Artificial Intelligence: Algorithms, Operational Environments and Hyperbole

A Monograph

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2018

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*
24-05-2018

2. REPORT TYPE
Masters' Thesis

3. DATES COVERED *(From - To)*
JUN 2017 – MAY 2018

4. TITLE AND SUBTITLE
Artificial Intelligence: Algorithms, Operational Environments and Hyperbole

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
MAJ Donald William Griesmyer III

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
U.S Army Command and General Staff College
ATTN: ATZL-SWD-GD
Fort Leavenworth, KS 66027-2301

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
School of Advanced Military Studies, Advanced Military Studies Program

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION / AVAILABILITY STATEMENT
Approved for Public Release, Distribution Unlimited

13. SUPPLEMENTARY NOTES

14. ABSTRACT
In the past two decades, artificial intelligence (AI) gained a lot of attention and inspired innovation across many fields of science. US military forecasters created numerous predictions of future operating environments with AI as a dominant feature. This paper reports on the historical trend of AI innovations leading to periods of high expectations for the emergence of a truly artificial general intelligence (AGI). These inflated expectations of continued innovation outpaced actual capabilities leading to disillusionment. Artificial intelligence goes through cycles of new innovations, over expectations, and disillusionment followed by modest advancement. The cyclical nature of AI innovation follows cycles of extreme hyperbole which, in past cycles, resulted in a loss of funding and the slowing of future innovations. To avoid future disillusionment and loss of progress, seen in the cycle of hyperbole, leaders need a realistic understanding of machine learning technology and what it will mean for future AI development. This paper presents a functional framework for understanding artificial intelligence's interaction with the operational environment.

15. SUBJECT TERMS
Army; Artificial Intelligence; Hyperbole; Hype-Cycle; Deep Learning; Machine Learning

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
					MAJ Donald William Griesmyer III
a. REPORT	b. ABSTRACT	c. THIS PAGE	(U)	54	19b. TELEPHONE NUMBER *(include area code)*
(U)	(U)	(U)			

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39.18

Monograph Approval Page

Name of Candidate: MAJ Donald W. Griesmyer

Monograph Title: Artificial Intelligence: Algorithms, Operational Environments and Hyperbole

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The opinions and conclusions expressed herein are those of the student author and do not necessarily represent the views of the US Army Command and General Staff College or any other government agency. (References to this study should include the foregoing statement.)

Abstract

Artificial Intelligence: Algorithms, Operational Environments and Hyperbole, by MAJ Donald W. Griesmyer, US Army, 54 pages

In the past two decades, artificial intelligence (AI) gained a lot of attention and inspired innovation across many fields of science. US military forecasters created numerous predictions of future operating environments with AI as a central feature. This paper reports on the historical trend of AI innovations leading to periods of high expectations for the emergence of a truly artificial general intelligence (AGI). These inflated expectations of continued innovation outpaced actual capabilities leading to disillusionment. Artificial intelligence goes through cycles of new innovations, over expectations, and disillusionment followed by modest advancement. The cyclical nature of AI innovation follows cycles of extreme hyperbole which, in past cycles, resulted in a loss of funding and the slowing of future innovations. To avoid future disillusionment and loss of progress, seen in the cycle of hyperbole, leaders need a realistic understanding of machine learning technology and what it will mean for future AI development. This paper presents a functional framework for understanding artificial intelligence's interaction with the operational environment.

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Acknowledgments

I would like to express gratitude to my wife, Sarah and seven children who have supported me with an extreme amount of patience and devotion.

Acronyms

AI	Artificial intelligence
ADM	Automated Decision-Making
AFC	Army Functional Concept
AGI	Artificial General Intelligence
AOC	Army Operating Concept
ARCIC	Army Capabilities Integration Center
ARL	Army Research Laboratory
CEO	Chief Executive Officer
CIO	Chief Investment Officer
CNN	Cable News Network
DARPA	Defense Advanced Research Projects Agency
DoD	Department of Defense
DOTMLPF	Doctrine, Organization, Training, Materiel, Leadership and Education, Personnel and Facilities
GPS	General Problem Solver
IADS	Integrated Air Defense System
IT	Information Technology
IBM	International Business Machine
LISP	Locator/Identifier Separation Protocol
MIT	Massachusetts Institute of Technology
OE	Operational Environment
PSCM	Problem-Space Computational Model
R&D	Research and Development
RAND	Research and Development
ROI	Return on Investment

Illustrations

Introduction

Semantics, technological optimism, misunderstanding, and agendas cloak the current debate about artificial intelligence (AI), and the nature of intelligence. Predictions about AI run the gamut from a dystopian Skynet apocalypse to an AI-driven utopia. AI and 'Machine Learning' may be on a path to disillusionment. Prominent experts in technology warn of the catastrophic effect AI will have on the future of humanity. Elon Musk, Chief Executive Officer (CEO) of Tesla and Space X, calls AI an existential threat and pleads for governments to regulate AI "before it is too late."[1] Steven Hawking, the late prominent physicist, argued that AI would be the end of humanity. News outlets run headlines such as "US Risks Losing Artificial Intelligence Arms Race to China and Russia."[2] Others invoke apocalyptical views and emotional responses to AI technology. For example, the New York Times recently published a headline, "The Pentagon's 'Terminator Conundrum': Robots That Could Kill on Their Own."[3] Unfortunately, fear-mongering statements resonate with the general public and builds on the pop culture narrative that AI will be the end of humanity.

When observed in historical context, current views towards AI follow a measurable trend with stages of technological development that Gartner, Incorporated, an information technology (IT) research "hype cycle," presented in Figure 1.[4] The hype cycle begins with a "technology trigger," a new conceptualized capability that only exists in prototypes, capturing media attention.

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[1] Samuel Gibbes, "Elon Musk: Regulate AI to Combat 'Existential Threat' before It's Too Late," *The Guardian*, July 17, 2017, accessed December 9, 2017, https://www.theguardian.com/technology/2017/jul/17/elon-musk-regulation-ai-combat-existential-threat-tesla-spacex-ceo.

[2] Zachary Cohen, "US Risks Losing Artificial Intelligence Arms Race to China and Russia," *CNN,* November 29, 2017, accessed December 9, 2017, http://www.cnn.com/2017/11/29/politics/us-military-artificial-intelligence-russia-china/index.html.

[3] Jacob Regenstein, "The Pentagon's 'Terminator Conundrum': Robots That Could Kill on Their Own," *New York Times,* October 26, 2016, accessed December 9, 2017, https://www.nytimes.com/2016/10/26/us/pentagon-artificial-intelligence-terminator.html.

[4] "Gartner Hype Cycle," Gartner Research Methodologies, accessed April 3, 2018, https://www.gartner.com/technology/research/methodologies/hype-cycle.jsp.

The next state is “peak of inflated expectations” where early adopters gain publicity for their successes in implementing the technology. The next stage is the “trough of disillusionment” when inherent physical limitations to technology becomes apparent and AI fails to mature and investment money moves to more promising ventures. After the trough of disillusionment, the technology continues to mature albeit at a much slower pace. In this slower environment, it is better understood, and implementation has real success. The final stage, the “plateau of productivity” is when there is broad implementation of the technology in well-understood conditions. Then industries create standards and regulations to govern the implementation and interoperability of the technology.

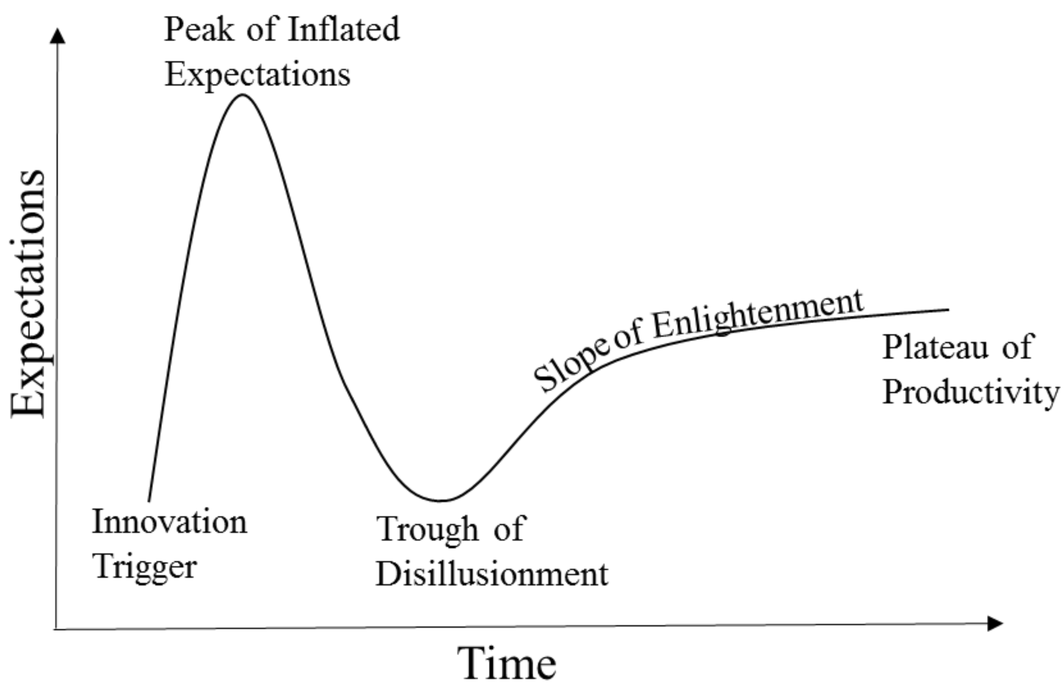

Figure 1. The Hype Cycle for Technological Development. “Gartner Hype Cycle,” Gartner Research Methodologies, accessed April 3, 2018, https://www.gartner.com/technology/research/methodologies/hype-cycle.jsp.

Previous evolutions of AI development followed the cycle of hyperbole with several peaks and troughs that will be outlined here. Each time AI development entered a trough of disillusionment and US government and military spending ceased funding; development of AI stalled. The US government and military have been an integral part of the history of AI's development and will continue to play a vital role in guiding future development. The US military cannot afford to have inflated expectations that precipitate a period of disillusionment that will cede initiative and technological advantage to US peer competitors, Russia and China; who are pursuing weaponized AI. Leaders and decision makers need a realistic technical understanding of AI development to guide them in their integration of AI into the Army enterprise. The past cycles of hyperbole provide examples of pitfalls to avoid but also of areas to look for useful applications and future innovations.

Literature Review

Artificial Intelligence Research Beginnings

The science of AI emerged from three important meetings. The first of which was the Sessions on Learning Machines held in Los Angeles, 1955. Researchers from the Massachusetts Institute of Technology (MIT) and RAND Corporation presented papers addressing machine systems learning abilities imitating the nervous systems' self-organization and learning processes.[5] The conference established the direction for using digital computers to build neural networks that imitate brain activity in areas of pattern recognition, image processing, and game playing.[6]

The second was a summer research project on AI proposed by John McCarthy and held at Dartmouth College in 1956. The two-month study endeavored to quantify the features of intelligence with the desire to program machines to formulate concepts, use language, and solve problems normally believed to require human-level intelligence. A significant output from the project was the understanding that the processing of symbolic structures, or "heuristics," were key elements in intelligent behavior and problem-solving. This project gave rise to a program called the "Logic Theorist," dubbed a "thinking machine" by its creators and seen at the time by a cognitive psychologist as capturing the "central process in human problem-solving."[7]

The third meeting held in 1958, was a symposium called Mechanization of Thought Process; sponsored by the National Physical Laboratory in the United Kingdom. This conference attracted academics researching various aspects of artificial thinking; pattern recognition, language translation, programming, and mechanization of industrial planning. Researchers

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[5] Willis H. Ware, "Introduction to Session on Learning Machines," in *Proceeding of the Western Joint Computer Conference* (New York: Association for Computing Machinery, 1955), 85.

[6] Ware, 85.

[7] Pamela McCorduck, *Machines Who Think*, 2nd ed. (Natick, MA: A K Peters, Ltd., 2004), 167-170; Herbert A. Simon and Allen Newell; "Human Problem Solving: The State of the Theory in 1970," *American Psychologist* 26, no. 2 (February 1971): 147.

Marvin Minsky (founder of MIT AI laboratory), John McCarthy (established Stanford's AI laboratory), and Oliver Selfridge (father of machine perception) presented foundational papers on methods of AI with heuristic and common sense programming along with "Pandemonium," a paradigm for processes with the ability to adapt and self-improve.

Minsky described different methods for the use of heuristics in programming for pattern recognition, machine learning, and future planning.[8] McCarthy developed a computer language incorporating computer friendly mathematical expressions in commonsense first-order logic.[9] Selfridge elaborated on the significance of parallel computing in performing calculations for pattern recognition.[10] These ideas proved to be the foundations for further advances in AI.

Balancing Optimism with Realty

From the beginning, AI researcher envisioned a fast-maturing technology. Their optimism inspired the public to expect that shortly, man and intelligent machines will live and work together. However, the technological realities of the 1950s did not meet expectations. In 2006, many of the founding and prominent AI researchers met at Dartmouth College to survey the last 50 years of AI achievements. McCarthy said then that the main reason AI advancements had not lived up to his expectations was that "AI is harder than we thought."[11]

History has shown that when it comes to new technology, whether clockwork from the 18th century or steam power from the 19th century, there was a common expectation that the new

[8] Marvin Minsky, "Some Methods of Artificial Intelligence and Heuristic Programming," in *Proceedings on the Symposium on Mechanization of Thought Processes*, vol. 1, ed. D.V. Blake and A. M. Uttley (London: Her Majesty's Stationery Office, 1959), 16-19.

[9] John McCarthy, "Programs with Common Sense," in *Proceedings on the Symposium on Mechanization of Thought Processes,* vol. 1, ed. D.V. Blake and A. M. Uttley (London: Her Majesty's Stationery Office, 1959), 77-80.

[10]Oliver Selfridge, "Pandemonium: A Paradigm for Learning," in *Proceedings on the Symposium on Mechanization of Thought Processes*, vol. 1, ed. D.V. Blake and A. M. Uttley (London: Her Majesty's Stationery Office, 1959), 513.

[11] Nils Nilsson, *The Quest for AI: A History of Ideas and Achievements* (Cambridge: Cambridge University Press, 2009), 80.

technology would create a machine with human-like general intelligence.[12] An artificial general intelligence (AGI) is capable of performing intelligent human action. AGI is also called "strong AI" compared to a narrowly or weakly applied AI with purpose-built algorithms for problem-solving and reasoning. The twentieth century was no different. The nascent digital computing with the initial advances in applying algorithms for game theory, logical reasoning, and mathematical computations spurred hope for the evolution of machine intelligence. Scientists saw the computer's potential and started investigating algorithmic applications of speech recognition, natural language processing, image recognition and machine-control.

The scientific theories along with researchers' promises of an AGI outpaced actual computing hardware capabilities. The industry's hubris led to several boom-bust cycles, where the money for research was plentiful with the expectations of big advances in AI. However, as these advances stalled, research funds dried up. Logic and computational theory advances faster than what is physically capable through technology. The theoretical possibility of what a machine could do through applied logic was a powerful motivator for pushing AI technological development. However, hardware development comes in the form of punctuated equilibrium. The irregular bursts of activity divided AI development into three periods of activity resembling the Gartner's hype cycle. The first two periods of AI development make significant strides forward in research but with unrealized expectations resulted in the trough of disillusionment, called an AI winter, which is characterized by research stagnation and lack of funding.[13] Today's AI is in the third period of development.

The first boom started during the Cold War with high expectations for algorithms capable of machine translation and database manipulation. By the mid-1960s researchers began to lose

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[12] Herbert L. Sussman, *Victorian Technology: Invention, Innovation, and the Rise of the Machine* (Santa Barbara: ABC-Clio, 2009), 38-45.

[13] Jim Howe, "Artificial Intelligence at Edinburgh University: A Perspective; The Nature of Artificial Intelligence," The University of Edinburgh, School of Informatics, last modified June 2007, accessed April 09, 2018, http://www.inf.ed.ac.uk/about/AIhistory.html.

confidence in AI's ability to continue to progress; leading to a collapse in funding by the 1970s. This led to the start of the first AI winter, which was marked by broad public disappointment with AI.

Advances in computer hardware and programming languages brought new life to the prospects of AI through the corporate adoption of expert systems in the early 1980s. However, by 1987 desktop computing precipitated the collapse of the purpose-built microcomputer, expert system. The end of the expert system in consort with the Japanese failure to produce a 5th generation computer ushered in the second AI winter. The disillusionment for AI lasted throughout the 1990s and well into the first decade of the 21st century.

However, as computing power and demand for robotic applications increased, research began to move forward but under different labels, attempting to avoid the stigma of the previous cycles of hyperbole. Some of the practical advances came in the form of industrial robots and machine translation. The practical advances lead to more advances in speech recognition, data mining, and information retrieval algorithms, such as Google's search technology. As non-technical users became familiar with machines that could perform tasks previously viewed as requiring human intelligence, users no longer viewed computing progress as moving towards an AGI.

Three Major Research Periods

The first period of AI research from 1952 to 1969, was a time of enthusiasm for intelligent machines coupled with great expectations for progress.[14] Allen Newell and Herbert Simon, researchers from the Rand Corporation and Carnegie Institute of Technology, built upon their earlier success with reasoning programs and developed the General Problem Solver (GPS) which was designed to model human problem-solving methods incorporating heuristics to solve

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[14] Stuart Russell and Peter Norvig, *Artificial Intelligence: A Modern Approach,* 3rd ed. (Saddle River, NJ: Prentice Hall, 2009), 19.

simple logic problems.[15] Success with GPS came with no small amount of hubris towards the prospects of a general AI. Simon, in 1957, announced,

> It is not my aim to surprise or shock you—but the simplest way I can summarize is to say that there are now in the world machines that think, that learn and that create. Moreover, their ability to do these things is going to increase rapidly until—in a visible future—the range of problems they can handle will be coextensive with the range to which the human mind has been applied.[16]

This quote accompanied other statements that claimed that within ten years, machines would solve mathematical theorems and beat chess champions.[17] The algorithms were showing promise for simple manipulation of data structures, yet resoundingly failed when trying to scale to larger more difficult manipulation of data. Initially, researchers thought AI programs could solve any problem just through scaling; harder problems would only need faster processor speeds and larger memories. "The fact that a program can find a solution in principle does not mean that the program contains any of the mechanisms needed to find it in practice."[18] In 1966, the Automatic Language Processing Advisory Committee (ALPAC 1966) authored a report describing the poor near-term prospects for AI in machine translation.[19] The negative review published by ALPAC caused support to sour towards AI research. Joel Moses, an MIT computer scientist who was a student under Marvin Minsky, said, "1967 was the turning point in my mind when there was enough feeling that the old ideas of general principles had to go…the old ideas were dying."[20] In 1969 the Mansfield Amendment caused Defense Advanced Research Projects Agency (DARPA)

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[15]Allen Newell, J. C. Shaw, and Herbert Simon, *Report on a General Problem-Solving Program* (Santa Monica: The RAND Corporation, 1959), 13.

[16]Russell and Norvig, 20-21.

[17] McCorduck, 116-118.

[18] Russell and Norvig, 21.

[19] John Hutchins, "ALPAC: The (In)famous Report," *MT News International*, no. 14, (June 1996), 9-12.

[20] McCorduck, 266.

to redirect their funding away from AI research.[21] The discord among researchers along with a scarcity of funding ushered in the first AI winter.

The second period of progress for AI or "boom times" came from 1975 to 1985. [22] The next wave of research focused on advances in knowledge representation with a clear distinction between algorithms with programming knowledge and special purpose rules, and algorithms aimed at AGI reasoning. The new methods of representing expert knowledge offered solutions to specific real-world problems.

Industries began automating expert knowledge, enabling faster data retrieval times reducing the need for human experts at significant cost savings. Economics drove almost "every major US corporation to have its own AI group…either using or investigating expert systems."[23] The Japanese Ministry of International Trade and Industry, in 1981, established a Fifth-generation computer project to build computers with AGI. US technology companies responded by establishing the Microelectronics and Computer Technology Corporation consortium, to remain competitive by developing their own AGI systems.[24] The ambitious efforts to develop AGI computing failed to materialize because of hardware and software limitations; primarily processing speeds, data storage and retrieval, and network configurations. Again, AI fell prey to a cycle of hyperbole where the physical limitations could not keep pace with excessive expectations about future AI capabilities. In the period of disillusionment, the majority of companies slashed funding for AI; starting the second AI winter.

The term "artificial intelligence," became a byword for failure, causing research to have to develop AI under different labels, closely integrated with computer science. AI methods

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[21] Nils Nilsson, *The Quest for AI – A History of Ideas and Achievements* (Cambridge: Cambridge University Press, 2010), 343.

[22] Nilsson, 343.

[23] Russell and Norvig, 24.

[24] Edward Feigenbaum and Pamela McCorduck, "The Fifth Generation: Japan's Computer Challenge to the World," *Creative Computing* 10, no. 8 (August 1984): 103.

continued to develop without being called AI. Industry and governments looked to high-performance computing (HPC) for progress instead of AI solutions. Industries put money towards research to improve computing hardware, user interfaces, data methods, and productivity. Researchers scaled down their ambitions for AI and applied algorithmic technology only when it added value to computing systems.[25] Progress in AI technology continued to develop albeit at a slower pace.

By the start of the 21st century, the third period of AI development began as a result of advances in commercial applications for machine learning, image recognition, text translation and natural language processing. The new period of development brought AI back into public discourse. Advances in probabilistic inference algorithms and neural networks coupled with deep learning techniques brought new hopes of achieving an AGI.[26] The new algorithms' performance in tasks that appeared to need human intelligence had philosophers questioning what truly defines human intelligence.

Achieving Artificial Intelligence

A problem with trying to define AI is that researchers do not agree on a definition of human intelligence; which AI is supposed to emulate. Linda Gottfredson, professor emeritus of educational psychology at the University of Delaware, performed a study showing that psychologists disagree on an accepted definition of human intelligence.[27] In 1996, the American Psychological Association formed a task force addressing the same question; could there be an agreement for a definition of human intelligence? The task force report uncovered, "when two dozen prominent theorists were recently asked to define intelligence; they gave two dozen

[25] Nilsson, 429.

[26] Russell and Norvig, 24-30.

[27] Linda S. Gottfredson, "Mainstream Science on Intelligence: An Editorial with 52 Signatories, History, and Bibliography," *Intelligence* 24, no. 1 (Jan-Feb, 1997): 13-23.

somewhat different definitions."[28] The task force concluded that there were "many ways to be intelligent," along with different ways to look at intelligence.[29] The difficulty in measuring intelligence has cascading effects on what we know about wisdom, creativity, practical knowledge, and social skill.[30] Robert Serpell, Professor of Psychology at the University of Zambia, claims intelligence is an aspect of the human mind that is a cultural construct of society.[31] Even if there was a scientific consensus on intelligence, it does not mean it will be accurate or useful.

Pulitzer Prize winner, Douglas Hofstadter said, "Once some mental function is programmed, people soon cease to consider it… 'real thinking.' The…core of intelligence is always in the next thing not yet programmed.[32] Philosophy professor, Vincent Müller from Anatolia College echoes the difficulties of the moving benchmark for machine intelligence in Larry Tesler's Theorem: "Intelligence is whatever machines have not done yet." [33] With the sliding scale for comparing AI against human intelligence, it would be like trying to make airplanes to fool birds.[34] Advancement in human flight came about when developers stopped trying to imitate birds and looked to understand aerodynamics.

A more promising approach is to base AI on models of the human brain developed by cognitive scientists working on algorithms following human reasoning steps. Another approach to AI is through creating precise formulations of problems for algorithmic computation. The

[28] Ulric Neisser et al., "Intelligence: Knowns and Unknowns," *American Psychologist* 51, no. 2 (Feb 1996): 77.

[29] Neisser et al., 95.

[30] Neisser et al., 96.

[31] Robert Serpell, "The Cultural Construction of Intelligence," *Psychology and Culture*, ed. Walter J. Lonner and Roy S. Malpass (New York: Pearson, 1994), 163.

[32] Hofstadter, 601.

[33] Vincent C. Müller, "New Developments in the Philosophy of AI," in *Fundamental Issues of Artificial Intelligence*, ed. Vincent C. Müller (Cham, Switzerland: Springer International Publishing, 2016), 3.

[34] Russell and Norvig, 3.

downside is all problems need reduction to logical notation. The most promising approach to AI is to create algorithms that generate the best probable solutions through various mechanisms of rationality.[35] AI innovations thus far include combinations of rational mechanism in software and hardware.

The benefits of applying AI algorithms to new problems seems endless. Currently, there are hours of TEDx talks with experts claiming the current AI trend is different and to expect an AGI that will match or surpass human cognition. One of these experts is Nick Bostrom, a philosophy professor at Oxford, where he describes that in twenty years there will be a super-intelligent AI with a "super-human level of general intelligence."[36] He claims twenty years is close enough to be concerned about AI today yet long enough to account for new breakthroughs and to allow developers to find simple solutions to hard problems.[37]

Bostrom sees several paths to achieve superintelligence. The first is to "simply replicate the relevant evolutionary processes on Earth that produced human-level intelligence."[38] Another method for super-intelligent machines can come from a whole brain emulation by creating a detailed model of a person's brain recreating the exact neural network. With powerful enough hardware and an exact 3D model of the person's brain, "the result would be a digital reproduction of the original intellect, with memory and personality intact."[39] Bostrom sees whole brain emulation only depending on technical capability allowing computers to match or surpass the brain in neurons and processing speed.[40]

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[35] Russell and Norvig, 4.

[36] Nick Bostrom, *Superintelligence* (Oxford: Oxford University Press 2014), 39.

[37] Bostrom, 19.

[38] Bostrom, 42.

[39] Bostrom, 48.

[40] Bostrom, 51.

Artificial Intelligence Challenges

Since the enlightenment philosophers still debate the relationship between human cognition and machine computation. Journalist George Johnson, author of *Machinery of Mind: Inside the New Science of Artificial Intelligence*, described the fundamental assumptions of AI is that the human mind is a formal system for manipulating symbols representing the environment. “it doesn’t matter what the brain is made of…Using the right software, one system (the mind) can be mapped into the other.”[41]

Earlier in the evolution of AI, there was more of a dialectical view of AI and the prospects of the relationship of the mind to the machine. A professor of philosophy, Alan Anderson pondered where the separation between the mind and the machine existed. He offered two extreme opposing positions to the dialogue.

> 1. We might say that human beings are merely very elaborate bits of clockwork, and that our having "minds" is simply a consequence of the fact that the clockwork is very elaborate.
> 2. We might say that any machine is merely a product of human ingenuity (in principle nothing more than a shovel), and that though we have minds, we can't impart that peculiar feature of ours to anything except our offspring: no machine can acquire this uniquely human characteristic.[42]

Today most in the AI community would lean towards the first position.[43] Some mathematicians, scientist, and philosophers offer theories that support the argument against a mechanical mind offered in position two. The arguments against a mechanical mind and thus against AGI involve the inherent limitations of algorithmic computations.

Computer scientist David Harel, at the Weizmann Institute of Science, authored *Computers Ltd.: What They Really Can't-Do,* where he describes what he calls the “bad news” of computing which are “proven, lasting and robust…problems that computers are simply not able

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[41] George Johnson, *Machinery of Mind: Inside the New Science of Artificial Intelligence* (New York: Random House, 1986), 250.

[42] Alan Ross Anderson, *Minds and Machines* (Englewood Cliffs, NJ: Prentice-Hall, Inc., 1964), 2.

[43] Nilsson, 382.

to solve, regardless of…hardware, software, talents or patience."[44] For AI to solve a problem, it must first have an appropriate algorithm that provides "correct outputs for all legal inputs."[45] This algorithm requires routines programmed with all the intended meanings for input. The tasks given to the algorithm to perform must be unambiguous and explicitly detailed.

At the machine level, the algorithm will execute all legitimate inputs and attempt to find a rule-based output.[46] Even with the a priori conditions met, there is no way to determine the time needed for an algorithm to solve a problem, or where the algorithm is at in the calculation including if it will compete the calculation (self-terminate or halt) with a correct output.[47] Once an AI algorithms start a computation, it cannot self-terminate if a problem turns out to be unsolvable. Turing first envisioned "the halting problem," proposing the impossibility to predetermine an algorithm's ability to finish a calculation.[48] The halting problem is part of a larger problem in computability theory known as Rice's Theorem; which describes that the non-trivial properties of an algorithm are undecidable, meaning that "nothing about computation is computable!"[49] Additional problems arise for algorithms when they do self-terminate but produce an erroneous output. The algorithm cannot determine if the output is correct or the intended result independently.[50]

In addition to the algorithm computation, AI has limitations based on the formal system structuring the algorithm. Kurt Gödel, the twentieth-century mathematician, and philosopher

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[44] David Harel, *Computers Ltd.: What They Really Can't Do* (Oxford: Oxford University Press, 2000), viii.

[45] Harel, 16.

[46] Harel, 16-20.

[47] Harel, 26,48, 56-58.

[48] S. Barry Cooper and Jan van Leuven, *Alan Turing: His Work and Impact* (Amsterdam: Elsevier, 2013), 209.

[49] John E. Hopcroft, Rajeev Motwani, and Jeffrey D. Ullman, *Introduction to Automata Theory, Languages, and Computation*, 2nd ed. (Boston: Addison-Wesley, 2001), 388; Harel, 54.

[50] Harel, 78.

formulated the incompleteness theorem which postulates that “truth transcends theoremhood, in any…formal system.”[51] Within any formal, complex, self-referencing system, some statements are unprovable in that system. Based on the incompleteness theorem, AI’s algorithmic system may encounter problems that are unsolvable in that system’s frame of reference. John Lucas, a Merton College Fellow at Oxford University, used Gödel’s incompleteness theorem to argue against the idea that a machine could have a mind because it would require the machine to question its processes and reflect on what it can and cannot do.[52] The human mind can resolve conflicts in self-referencing logic, whereas an algorithm currently cannot.

Gödel’s incompleteness theorem translates Epimenides paradox, involving self-referencing logic, “All Cretans are liars,” or “This statement is false” into a mathematical expression.[53] The human mind unconsciously filters through millions of patterns sorting through features and options for action. Although machines are excellent at processing per an algorithm, they cannot independently determine rules for action. AI needs a predefined frame for addressing the secondary and irrelevant incidents and possibilities that occur in a complex reality. This framing problem requires AI to have rules, heuristics set by a human to cope with infinite possibilities. In short, AI is following instructions set by humans in an artificially constrained environment.

Artificial Intelligence Critics

If AI research groundbreakers, Minsky, Newell, and Simon were overly optimistic about AI’s capabilities, then the late, Hubert Dreyfus, a philosophy professor at the University of California Berkeley, was equally confident in what AI could not do. While as a consultant for

[51] Douglas R. Hofstadter, *Gödel, Escher, Bach: An Eternal Golden Braid* (New York: Basic Books, 1999), 86-87.

[52] John R. Lucas, “Minds, Machines and Gödel,” *Philosophy* 36, no. 137 (April – July 1961): 124.

[53] Hofstadter, 19.

RAND Corporation, he did a study called "Alchemy and Artificial intelligence" in 1965, attacking AI with comparisons to the pseudo-sciences in the Middle Ages.

In 1972, Dreyfus published a book called *What Computers Can't-Do; A Critique of Artificial Reason* which describes the naivety of the assumption that "human and mechanical information processing ultimately involve the same elementary processes."[54] Dreyfus argues against the assumption that it is possible to formalize all knowledge and express it in logical terms of Boolean functions. Further, he claims that algorithms presuppose that all information about the environment that is essential to intelligent behavior are "analyzable as a set of situation-free determinate elements…logically independent of all the others."[55] In Dreyfus' view, AI research sought, "the discovery of rules—rules for moral behavior, rules of intellectual behavior, and rules for practical behavior."[56]

Rule-based behavior does not give AI the ability to understand the meaning of knowledge. If the AI learns "red car = car + red" it does not intuitively know that the "red car is a red colored car." Dreyfus understood what is still called the symbol grounding problem.[57] Dreyfus' challenge of AI's philosophical assumptions pushed AI researchers to look for more scientific approaches to intelligent behavior.[58] Pamela McCorduck, documenting in her interviews with Minsky and Simon, offers a unique take on Dreyfus' work,

> The funny thing is that both sides might turn out to be more or less right. It may indeed be that human intelligence in complete detail cannot be realized on a computer…But that doesn't preclude the possibility that machines may eventually exhibit intelligent behavior.[59]

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[54] Hubert Dreyfus, *What Computers Can't-Do: A Critique of Artificial Reason* (New York: Harper & Row, 1972), 67.

[55] Dreyfus, 68.

[56] McCorduck, 211.

[57] Dreyfus, 203.

[58] McCorduck, 239.

[59] McCorduck, 239.

Dreyfus philosophical opposition to AI is a counterbalancing effect to the hubris of Minsky, Newell, and Simon.

Max Tegmark, a professor at Massachusetts Institute of Technology, provides a balanced approach to AI's philosophical debate. He describes that in addition to asking if AGI is achievable we should also ask what it will mean. Tegmark explains that AI experts are in one of three schools of thought; those who are skeptical, those who see it as beneficial, and those who claim AI to be the coming of a digital utopia. There will always be Luddites opposing any technology replacing humans. Tegmark created a matrix representation of the spectrum of different positions and their relationship to when they think AGI will arrive and whether it will be beneficial, in Figure 2. The current forecast for AI goes "from confident optimism to serious concern."[60] The range for when an AGI will arrive goes from decades to centuries.

[60] Max Tegmark, *Life 3.0: Being Human in the Age of Artificial Intelligence* (New York: Alfred A. Knopf, 2017), 30-31.

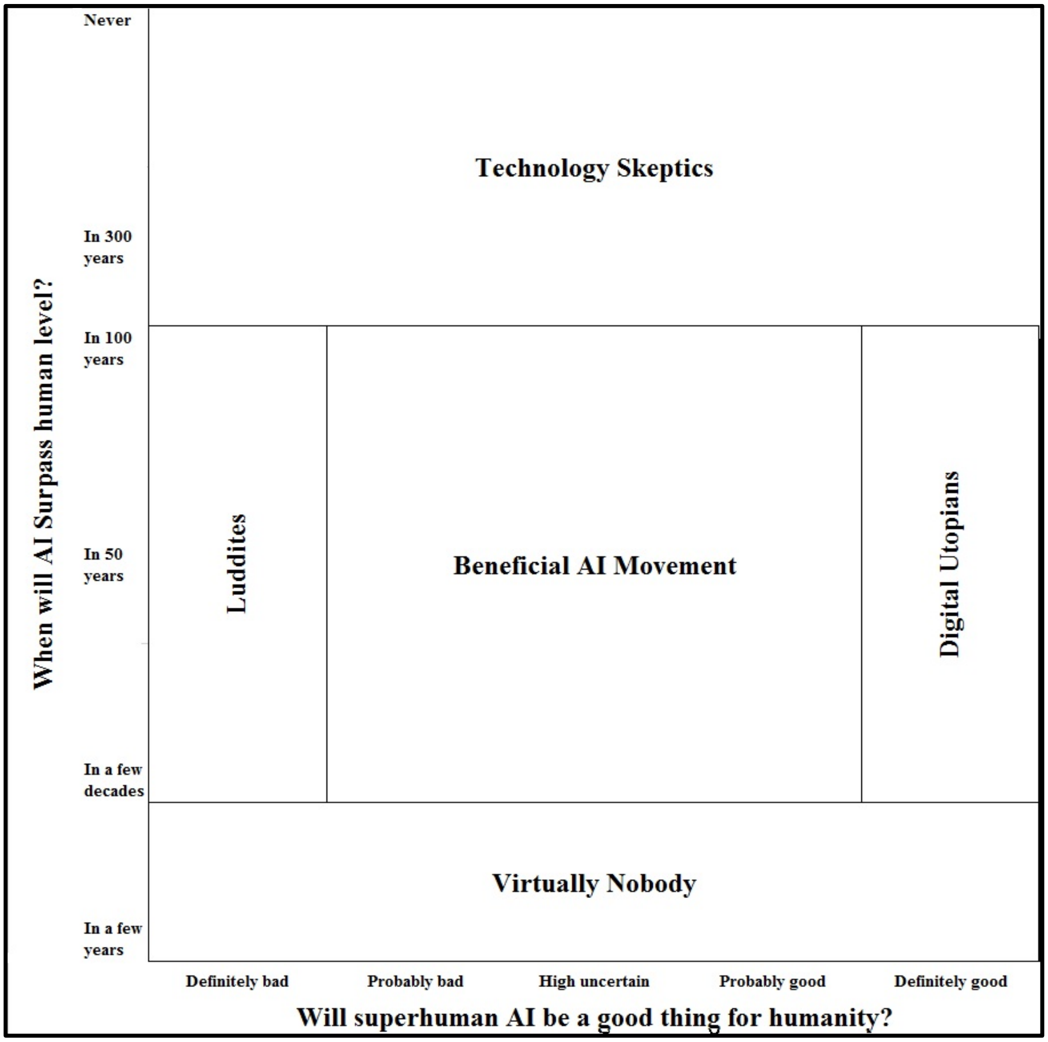

Figure 2. Mac Tegmark's Matrix of Philosophical Positions. Max Tegmark, *Life 3.0: Being Human in the Age of Artificial Intelligence* (New York: Alfred A. Knopf, 2017), 30-31.

Artificial Intelligence Problem Solving

As seen in early developmental phases of AI, researchers and industry need to continue set realistic goals for AI. The goals need to take into account the inherent limitations of computing without overpromising capabilities. In Stuart Russell's and Peter Norvig's foundational text, *Artificial Intelligence: A Modern Approach*, they identify that continued advances in AI will arrive by focusing on creating intelligent agents. What makes these agents intelligent is their rational actions derived from rational decision making from environmental inputs.[61] The intelligent agent is an AI algorithm designed to solve a problem, instead of an AI that is designed to mimic human behavior. The desire should be in trying to create intelligent agents that act rationally which may include using human problem-solving methods to arrive at rational decisions.

Herbert Simon, an economist and political scientist, working with Allen Newell, computer and cognitive scientist, present an information-processing theory of rational human problem solving, which provides a framework for understanding a method of AI problem-solving. As a problem solver, AI is fundamentally an information-processing system. The "task environment" is the way a programmer describes the problem that the algorithm is to solve. The "problem space" is the cognitive structure that the AI will use to represent the task environment for problem-solving.[62] The AI and task environment define the problem space regarding the problem state. Included in the problem space, are the operations the AI needs to perform to change the problem from one state to another and what functions the AI will use to evaluate the change of state.[63] A problem space represents the "possible states of knowledge" that an AI might attain, and the state of knowledge represents what the AI "knows about the problem" at any particular time.[64]

Newell and Simon identified with the early GPS program, a roadmap for future iterations of problem-solving algorithms.[65] John Laird, building upon the work of Newell and Simon on the GPS, developed a cognitive architecture for problem spaces named Soar. Soar is a comprehensive cognitive architecture for the organization of knowledge and behavior for rational agents

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[61] Russell and Norvig, 30.

[62] Herbet A. Simon and Allen Newell, "Human Problem Solving: The State of the Theory 1970," *American Psychologist* 26, no. 2, (Jan 1971): 151.

[63] Vinod Goel and Peter Pirolli, "The Structure of Design Problem Spaces," *Cognitive Science* 16, no. 3 (July 1992): 399.

[64] Simon and Newell, 151.

[65] Allen Newell, John C. Shaw and Herbert A. Simon, *Report on a General Problem-Solving Program* (Santa Monica: The RAND Corporation, 1959), 26-28.

functioning at the human level.[66] Soar is an example of many ways researchers create a problem-space computational model (PSCM). The PSCM provides a fixed framework for controlling AI's behavior through multi-levels deliberation across hierarchical representations of goals and meta-cognitive knowledge.[67] Creating a general fixed framework is an effort to address AI framing problems and characterize the task environment.

Researchers looking for methods to achieve AI, use PSCMs, in developing machine learning for pattern recognition, which involves categorizing data into different classes. The process of machine learning uses a probabilistic statistical model to predict the appropriate classification for unknown data based on previously learned rules or heuristics. Humans have great difficulty in mathematically categorizing multi-dimensional data. Machine learning algorithms parameterize patterns into a number vector or matrix. Machine learning algorithms apply the pattern data to different data categories by changing matrix dimensions.[68] A task easy for algorithms but not so easy for humans to do computationally.

Is machine learning truly intelligent learning? Edsger Dijkstra, the computer scientist, speaking at the 1984 Association for Computing Machinery conference, presented a commentary about the negative detractors towards efforts to develop AI. Dijkstra describes Alan Turing's attempt to create criteria defining the threshold for a thinking machine is "about as relevant as the question of whether submarines can swim."[69] Russell and Norvig elaborated on his statement by defining the word "swim" from the American Heritage Dictionary. The authors identified that the definition of "swim" is a movement through water by "limbs, fins or tails," yet most people

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[66] John Laird, *Soar Cognitive Architecture* (Cambridge, MIT Press, 2012), 43.

[67] Laird, 47-59.

[68] Yusuke Sugomori, et al., *Deep Learning: Practical Neural Networks with Java* (Birmingham, UK: Packt, 2017), chap. 1, section 2, electronic publication.

[69] Edsger W. Dijkstra, "The Threats to Computing Science," (keynote address at the ACM 1984 South Central Regional Conference, Austin, The University of Texas at Austin, November 16-18, 1984), accessed April 9, 2018, http://cs.utexas.edu/users/EWD/transcriptions/EWD08xx/EWD898.html.

would agree that a limbless submarine cannot swim. However, when it comes to airplanes most would agree that they fly. When in reality neither definition has any bearing on the how it is designed or used.[70] It does not matter that machine learning will not become an AGI because there is great utility in "pattern classification and prediction based on input data."[71] Practical approaches to AI have brought about some very useful algorithms. Future advances will come out of utility versus the possibility of AGI.

Artificial Intelligence's Third Period of Development

Machine learning triggered AI's third period of development in the early 2000's which followed Gartner's hype cycle. Machine learning is dependent on large data sets, and without them, machine learning began entering into the trough of disillusionment. As the internet became prolific, the availability of open data grew exponentially. The recognition of massive amounts of open data, "Big Data," on the internet started a second peak in the hype cycle breathing new life into machine learning. When large data sets and machine learning started the downward slope after over-hyped expectations, innovation in neural networks and deep learning started the third peak in the hype cycle. These peaks of innovation leave open the question of whether deep learning will precipitate a period of disillusionment or will another innovation trigger the continued hope for machines with general intelligence?

For decision makers directing the integration of AI, it is important to know where AI is along the hype cycle. An understanding of the past developmental challenges and limitations offers a way to qualitatively parse the hyperbole. Over the past six decades, AI has been through many cycles of inflated hyperbole. The reality of AI's narrow, asymmetric progress coupled with unrealized hopes led to protracted periods of disillusionment. Currently, deep learning algorithms

[70] Russell and Norvig, 1021.

[71] Sugomori et al., chap. 1, section 3, electronic publication.

with training data have difficulty scaling and generalizing to other problem sets. Which still leaves AI algorithms too narrowly focused and unable to make intelligent meta-decisions.

Researchers, developers and integrators need to manage expectations throughout the hype cycle to avoid disillusionment. Significant disillusionment leads to extended periods of resources directed away from AI development ultimately delaying advancement of useful algorithms. Military, government and for profit organizations need methods to evaluate AI's capabilities. It is difficult to generalize on AI because each algorithm is designed to solve specific problems. However, it is possible to characterize AI based off how they represent their task environment through their problem spaces.

Methodology

This paper will use an inductive approach to develop a model for qualitatively evaluating AI, its problem spaces, and relationships to task environments. The historical narrative of AI's development provides the initial technical conditions and path dependencies for continued innovation. The theoretical model is an amalgamation of sense-making devices assembled to characterize technology's relationships to other systems.

The Artificial Intelligent Algorithm

This paper makes three critical assumptions about AI's limitations:

- There is a frame problem where an algorithm cannot self-identify the knowledge needed to solve a problem.
- There is a symbol grounding problem where algorithms understand a symbol as defined and not the concepts that put one symbol with another.
- There is a feature engineering problem where an algorithm cannot independently identify what feature about an object or phenomena to focus on and the requisite information needed for understanding the object or phenomena because doing either would violate the frame problem or the symbol problem.

Because of these limitations, AI functionality within operational art requires human input to identify the appropriate machine learning algorithms, features and model parameters that apply to a specific problem. The application of machine learning in the operations process will consist of recursive training and testing until achieving the desired output. AI will need a human to provide the cognitive links between tactical actions and strategic objectives. Realistic expectations for AI will depend on how operational artists quantify the elements of operational art in a logical framework facilitating algorithmic computation.

The Task Environment

International Business Machine (IBM) developed a "sense-making device" called the Cynefin framework. [72] The Cynefin frame work is a method to categorize knowledge for information processing. Developers of AI create a problem space that characterizes a task environment for an algorithm. Problem spaces are a cognitive framework representing knowledge and structure of the environment. The AI does not care about the task environment it will act on the provided inputs for the task environment and processes the input based on the problem space framework. The Cynefin framework provides a general method to characterize operational task environments and the nature of the problem spaces where AI will function. The value of the Cynefin framework is that it has broad recognition as a method to categorize knowledge for information-processing systems.

This paper will use a "taxonomy of levels of technological function" created by Arizona State University professors, Braden Allenby, professor of law and environmental science, and Daniel Sarewitz, professor of science and society, to describe the interaction between AI task environments.[73] Allenby and Sarewitz explain that cultures make choices that shape the purpose and development of their technologies. Societal choices affect the advancement of technology, and the advancement of technology affects the physical, cultural and political environment. To understand the recursive relationship between society and its technology there needs to be a method to describe the function of technology and its interconnectedness to the environment.

AI Functional Framework

This paper combines the Cynefin framework along with Allenby and Sarewitz's taxonomy to create a model called, AI functional framework (AIFF). The AIFF in this paper will

[72] Cynthia F. Kurtz and David J. Snowden "The New Dynamics of Strategy: Sense-Making in a Complex and Complicated World," *IBM Systems Journal* 42, no. 3 (February 2003): 462.

[73] Braden Allenby and Daniel Sarewitz, *The Techno-Human Condition* (Cambridge: MIT Press, 2011), 36.

categorize an AI algorithm's capability and its corresponding problem space according to the Cynefin framework at the different levels of technology defined by Allenby and Sarewitz. The functional framework will offer a graphical representation for conceptualizing AI's physical and cognitive relationship and capability. The framework offers a method to gauge AI's current state against a future state. Identifying the differences between past to possible future states concerning time offers a gauge to compare where AI is along the curve depicting the hype cycle.

I will be looking at AI integration through the lens of the Cynefin model combined with a taxonomy of technological function to create an AI functional framework, because the US Army needs to understand where its current understanding of AI is and the boom and bust cycle of America's infatuation with AI as our near-peer adversaries are forging ahead in this area.

Analysis

Questions

What is the operating environment for AI? What is a method of characterization for AI that will represent current functionality, and requirements for future innovations of AI? What are current uncertainties affecting AI's future development?

Objectives

Previous decades of AI research, any significant advances or new capability give way to excessive optimism followed by disappointment and another drought of funding until the next breakthrough. Executives responsible for technology investment and integration have the challenge to determine the appropriate level of funding for research and development (R&D) and timing the integration of technology into their organization. As seen in past evolutions, AI is vulnerable to inflated expectations. Excessive hyperbole misinforms the laymen public and politicians on the future of AI. Mass disillusionment toward AI from unmet expectations negatively impacts future innovations.

The object of this paper is to provide a generalized framework to reduce the complexities that characterize the state of AI capabilities and to highlight unrealistic expectations, risks, and limitation to future development. Army decision makers have a challenge in balancing conflicting demands for limited resources. Decisions for AI need to stand on a realistic understanding of what algorithms can do. Understanding AI's capabilities will assist in determining the most effective approach to addressing performance and cost objectives for AI.

Artificial Intelligence Future Operating Environment

Many of the current successes in AI stem from government and military spending. Today, AI sees an increased contribution from private investment. Government military funding towards AI is subject to political factors. Private funding for AI is dependent on perceived return on investment (ROI). The funding conditions are vulnerable to public disenfranchisement. Cracks are starting to form revealing evidence of over-hyped expectations for AI. In 2015 Facebook launched a general purpose personal assistant with much fanfare dubbed a supercharged AI. After two and half years Facebook has canceled the program for lack of usability and progress toward improved capability.[74] After several highly publicized fatal crashes, driverless cars are proving not to be infallible in understanding road and weather conditions or predicting actions of human pedestrians, cyclists and drivers, leaving many investors disillusioned.[75] Sensational news stories from a prominent scientist about the threat of an AI apocalypse, when added to investors reluctance to fund new projects, have many researchers questioning if AI will fall into the trough of disillusionment and experience another AI winter.

To quantify the current industries intent on integration of AI, Gartner Inc. surveyed 3,160 Chief Investment Officers (CIO) in ninety-eight countries. The results showed that AI initiatives were in the top-five funding priorities for the surveyed corporations. Chiraq Dekate, Research Director at Garnter Inc., assesses that by the year 2020 85% of the corporations will be in some form of buy, build or outsource for AI programs.[76] Figure 3, shows the results of the 2017 survey for 2018 AI deployment. Fifty percent of the respondents say they are either deploying or are planning to deploy AI. AI has the potential for widespread proliferation in the private sector, as long as the CIOs are planning with reliable data setting realistic objectives. Many of the CIOs in the survey claimed they were using poor or uncertain data to shape their planning efforts, while

[74] Cade Metz, "Facebook's Human-Powered Assistant May Just Supercharge AI," Business, *Wired*, September 26, 2017 accessed April 9, 2018, https://www.wired.com/2015/08/how-facebook-m-works/; Casey Newton, "Facebook Is Shutting Down M, Its Personal Assistant Service that Combined Humans and AI," Tech, *The Verge*, January 8, 2018, accessed April 9, 2018, https://www.theverge.com/2018/1/8/16856654/facebook-m-shutdown-bots-ai

[75] Aarian Marshal, "After Peak Hype, Self-Driving Cars Enter the Trough of Disillusionment," Transpiration, *Wired*, December 19, 2017, accessed April 9, 2018, https://www.wired.com/story/self-driving-cars-challenges/

[76] Laurence Goasduff, "2018 Will Mark the Beginning of AI Democratization," Digital Business, Smarter with Gartner, December 19, 2017, accessed April 5, 2018 https://www.gartner.com/smarterwithgartner/2018-will-mark-the-beginning-of-ai-democratization/.

others were struggling to understand AI's capabilities and did not think their organizations had the requisite skills to integrate AI properly.[77]

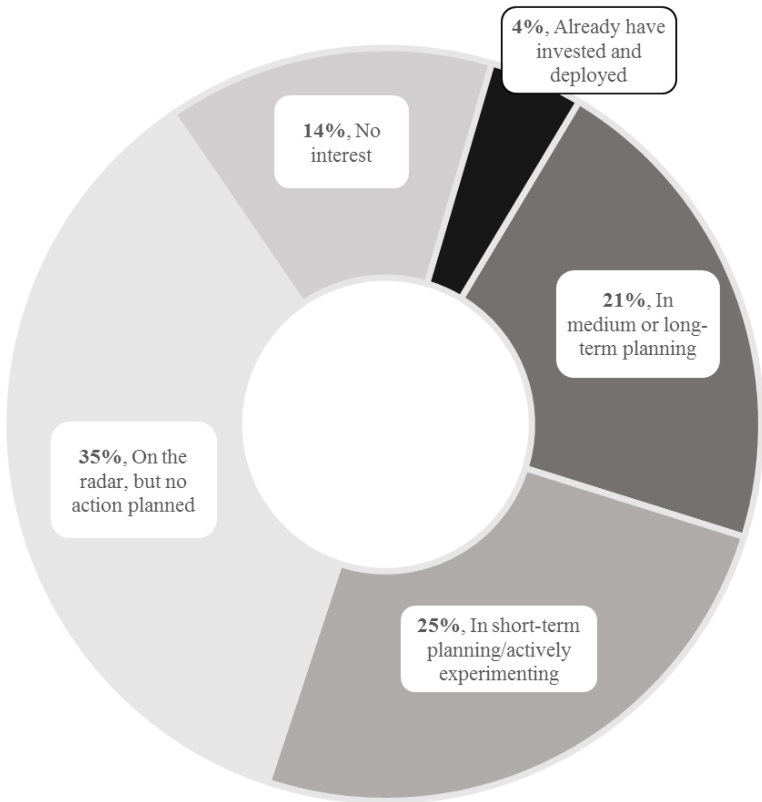

Figure 3. Results from Surveyed CIOs for 2018 AI Project Deployments. Laurence Goasduff, "2018 Will Mark the Beginning of AI Democratization," Digital Business, Smarter with Gartner, December 19, 2017, accessed April 5, 2018, https://www.gartner.com/smarterwithgartner/2018-will-mark-the-beginning-of-ai-democratization/

The data from the survey shows that roughly 80% of the CIO's are either planning or thinking about AI with only 4% deploying the technology. AI is in an early adoption phase of the current hype cycle which still leaves room for a significant number of these CIOs to become

[77] Laurence Goasduff "2018 Will Mark the Beginning of AI Democratization," Digital Business, Smarter with Gartner, December 19, 2017, accessed April 5, 2018, https://www.gartner.com/smarterwithgartner/2018-will-mark-the-beginning-of-ai-democratization/

disillusioned if they do not foresee an ROI due to planning on over-hyped or unreliable information.

Similarly, with industry's integration of AI for profit and efficiency, future battlefields will see AI's proliferation. The Army Capabilities Integration Center's (ARCIC) document, The Operational Environment (OE) and the Changing Character of Future Warfare, assesses that the future environment will have two critical drivers; one of societal change and the other of an evolving art of warfare, both spurred by breakneck advances in science and technology.[78] The pervasiveness of AI technology will see applications influencing every aspect of the future operating environment. Inflated expectations for AI involve extrapolation of capabilities across OEs without taking into consideration how the algorithm will interact with other rational agents in the OE.

As in previous iterations of AI development, recent innovations in AI applications give way to developers overpromising future capabilities of AI followed by years of technological abandonment. Each time AI development entered a trough of disillusionment and US government and military spending ended crippling AI development. The US government and military have been an integral part of the history of AI's development and will continue to play a vital role in guiding future development. The US military cannot afford to have inflated expectations that precipitate a period of disillusionment that will cede initiative and technological advantage to US peer competitors, Russia and China; who are pursuing weaponized AI. Leaders and decision makers need a realistic understanding of AI development to guide them in their integration of AI into the Army enterprise.

[78] Army Training and Doctrine Command G2, "The Operational Environment and the Changing Character of Future Warfare," Army Capabilities Integration Center, accessed April 21, 2018, http://www.arcic.army.mil, 2-4.

Operational Environment Translated into the Cynefin Framework

To avoid unrealistic expectations for AI's capabilities in the OE, the Cynefin framework offers a method to generalize the algorithms' OE. AI will execute tasks in the OE through algorithmic problem spaces, where it will sense the OE's current state and employ operators to attempt to change the OE to the desired state. The Cynefin framework consists of two knowledge domains which are a broad characterization of the AI's problem spaces for the OE. Figure 4, shows a graphical depiction of the Cynefin framework knowledge domains; one ordered and the other unordered. The knowledge domains contain quadrants, each with a unique context and

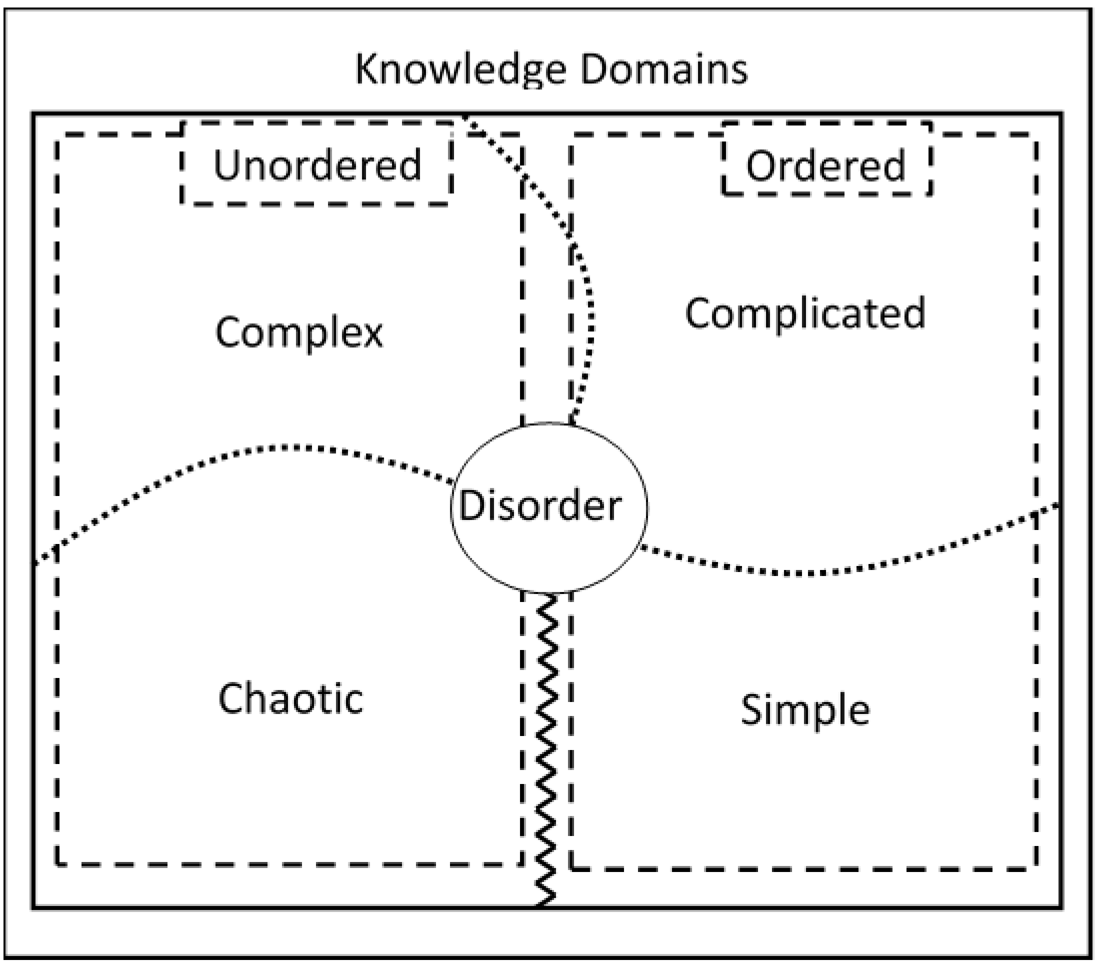

Figure 4. Cynefin Framework Knowledge Domains and Problem Space Quadrants. Cynthia. F. Kurtz and David J. Snowden "The New Dynamics of Strategy: Sense-Making in a Complex and Complicated World," *IBM Systems Journal* 42, no. 3 (February 2003): 462.

specific characterization of a problem space derived from the OE.[79] The quadrant problem spaces associate the "decisions, perspectives, conflicts and changes in order,"[80] that are unique combinations of rational choices and intentional action that an AI will need to manage to meet its designed objective successfully. The Cynefin ordered knowledge domain is an environment where the order is directed and can be described based on rules. The unordered knowledge domain is an environment where any order in the problem space is emergent and seeking equilibrium.[81] In the ordered domain there are two of the quadrants; one is a simple problem space, and the other is a complicated problem space. The unordered domain contains the remaining two quadrants; one is a complex problem space and the other is a chaotic problem space. In the center of the knowledge domain is 'disorder' which is the antithesis to both the unordered and ordered knowledge domain where any AI problem space does not relate to the task environment of the OE.

The OE is not specific to any quadrant problem space and is relative to the tasks the algorithm attempts to solve. The tasks environment can cross from one quadrant to another depending on the data and knowledge available to the algorithm. The boundary between the simple quadrant and the chaotic quadrant is precipitous and represents how an AI working in a simple problem space without careful attention to detail can fall into chaos quickly and dangerously.[82] Unlike the transition between the simple and chaotic quadrant transitions between the other three domains tend to have a more gradual transition.

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[79] David Snowden, "Complex Acts of Knowing: Paradox and Descriptive Self-Awareness," *Journal of Knowledge Management* 6, no. 2 (July 2002): 104.

[80] Kurtz and Snowden, 468.

[81] Kurtz and Snowden, 465.

[82] Kurtz and Snowden, 474-475.

Artificial intelligence knowledge domains

Each quadrant of the Cynefin framework represents a problem space that has a unique relationship with the task environment. The first and second quadrant are in an ordered knowledge domain, and the third and four quadrants are in an unordered knowledge domain. The simple and complicated problem spaces in the ordered knowledge domain are a product of directed order that is governed by rules. The unordered knowledge domain is where complex and chaotic problems are, represented in the third and fourth quadrants. In the unordered knowledge domain, general rules and principles do not apply.

Simple problem space

In the ordered domain, the simple and complicated quadrants are problem spaces; where researchers use the scientific methods to create a body of knowledge by empirical testing. The simple problem space is where cause and effect between actions and outcomes are known and predictable; relationships are quantifiable. With quantifiable relationships, standard operating procedures, predictive modeling, and process achieve consistency and efficiency. Decision-making in the simple domain consists of a function to sense input, categorize the data and respond based on defined procedures and best practices. The simple problem space models tasks with explicit methods and techniques.[83] AI in the simple problem space can easily outperform human cognitive abilities; these algorithms are examples of straightforward automation.

Complicated problem space

The second quadrant in the ordered knowledge domain is the complicated problem space where cause and effect are knowable. The connection between cause and effect are ambiguous, leaving a limited number of experts available to fully characterize the relationships. All elements in this problem space may translate to the simple problem space through expert knowledge, time and resources. The complicated problem space relies on experts and requires the ability to discern

[83] Kurtz and Snowden, 468.

between the contradictory opinions of competing experts. Experimentation, and interpretation to identify the properties and patterns of relationships dominate the complicated problem space.[84]

The defense industry has used AI in the complicated problems space for decades. An example of this was the US Army Artificial Intelligence Center's (AIC) Single Army Battlefield Requirements Evaluator (SABRE). This system helped decision-makers assimilate information and data that was only available to experts across warfighting functions. Analysts were unable to sort through the massive databases and extract relevant data for calculations to support "decisions on the Army's ability to provide the necessary forces to accomplish Desert Storm II."[85] The SABRE AI was a descriptive model that built alternative force structures, showing graphical command relationships and annotating detailed unit information. SABRE allowed decision makers to identify force readiness, modernization paths, and deployment dates. Planning processes that took days to complete would now only take hours.

SABRE demonstrated AI capability to function in the complicated problem space successfully. Advances in computing power, memory storage, and software have only given AI broader, cheaper and more accessible applications in the complicated problem space. Today individuals have access to AI tools and algorithms that were once only available to well-capitalized institutions. AI will continue to proliferate the complicated problem space and will be the primary domain of AI in the future. Developers will continue to use expert knowledge to find a way to quantify problems and pull tasks from the complex and chaotic environments into the complicated problem space for AI to solve.

Complex problem space

The third Cynefin framework quadrant is where complexity theory dominates. With complexity, cause and effect relationships are impossible to identify. The combined output from

[84] Kurtz and Snowden, 468.

[85] Patrick Lynch, David Elliott, and Michael Wilmer, "The Single Army Battlefield Requirements Evaluator (SABRE)," *Phalanx* 25, no. 2 (June 1992): 21.

independent actions of agents, whether human, machine or environmental in response to each other, resist any form of categorization.[86] The complex problem space is only understandable through retrospective coherence, hindsight of the systems emergent patterns and properties. Observation of the complex problem space has the potential to disrupt the entire system and if the system stabilizes there is no guarantee that it will continue it that state.[87]

It is in the complex problem spaces where the effectiveness or certainty of AI starts to break down. AI uses inference, and stochastic algorithms to model the complex task environment where results are relative and probabilistic. The impossibility to predict in complex problem spaces provides another challenge to fully autonomous AI. The dynamics of complex environments require near constant monitoring to detect changes of state. Depending on the nature of the problem space, an AI will need sensor systems to perceive state changes. The input from these systems can be faulty and vulnerable to noise and interference. Actuator control and goal-oriented planning algorithms are susceptible to perception issues that compound with sensing intervals and data processing limitations.[88]

The future use of AI in complex problem spaces relies on advances in knowledge representation, soft computing, genetic algorithms, and quantum computing. For AI to independently solve complex problems algorithms will need to combine first-order logic with probability, which is debatable if possible. The future of AI relies on the technical coevolution of society. Human-machine teaming provides a means to overcome the inherent limitations posed by

[86] Kurtz and Snowden, 466.

[87] Kurtz and Snowden, 469.

[88] Honghai Liu et al., *Robot Intelligence: An Advanced Knowledge Processing Approach* (London: Springer, 2010), v.

the framing and symbol grounding problems which will allow AI to solve problems with increasingly higher levels of complexity.[89]

Chaotic problem space

The chaotic quadrant is where any connection between cause and effect is unperceivable. The unsettled chaotic system represents consequences of abrupt changes within extreme disproportionate systems and structures. The goal of purposeful action in the chaotic problem space is to attempt actions that will nudge the system into another problem space. For an AI operating in a truly chaotic problem space, any probability or inference algorithm will fail to produce meaningful results.

For an AI to truly function in a complex or chaotic problem space, it will require an intelligence capable of overcoming the framing problem by axiom revision when faced with new data, and evaluating the validity of one's belief system. However, future AI operating in the chaotic problem space will need robust methods of addressing the frame problem, symbol problem, and the feature engineering problem. In addition to solving significant computational challenges, there are significant ethical considerations that need addressing for autonomous AI functioning in the complex and chaotic problem spaces.

Artificial Intelligence Levels of Function

AI not only operates in knowledge domains but also interacts with other rational agents and their problems spaces at different levels. Inflated expectations for AI come from not taking in account these levels of interaction. Allenby and Sarewitz' taxonomy of levels of technology offers a method to understand the recursive interplay between society and its technology. Technologies function and its interconnect with the environment is in three levels. The levels offer a quantifiable model to gauge AI's functional interaction with other systems and problem

[89] Klaus Mainzer, "Toward a Theory of Intelligent Complex Systems: From Symbolic AI to Embodied and Evolutionary AI," *Fundamental Issues of Artificial Intelligence*, ed. Vincent C. Müller (Cham, Switzerland: Springer, 2016), 256-257.

spaces. Figure 5, is a graphical representation of the different levels of technology and their functional interaction with other systems.

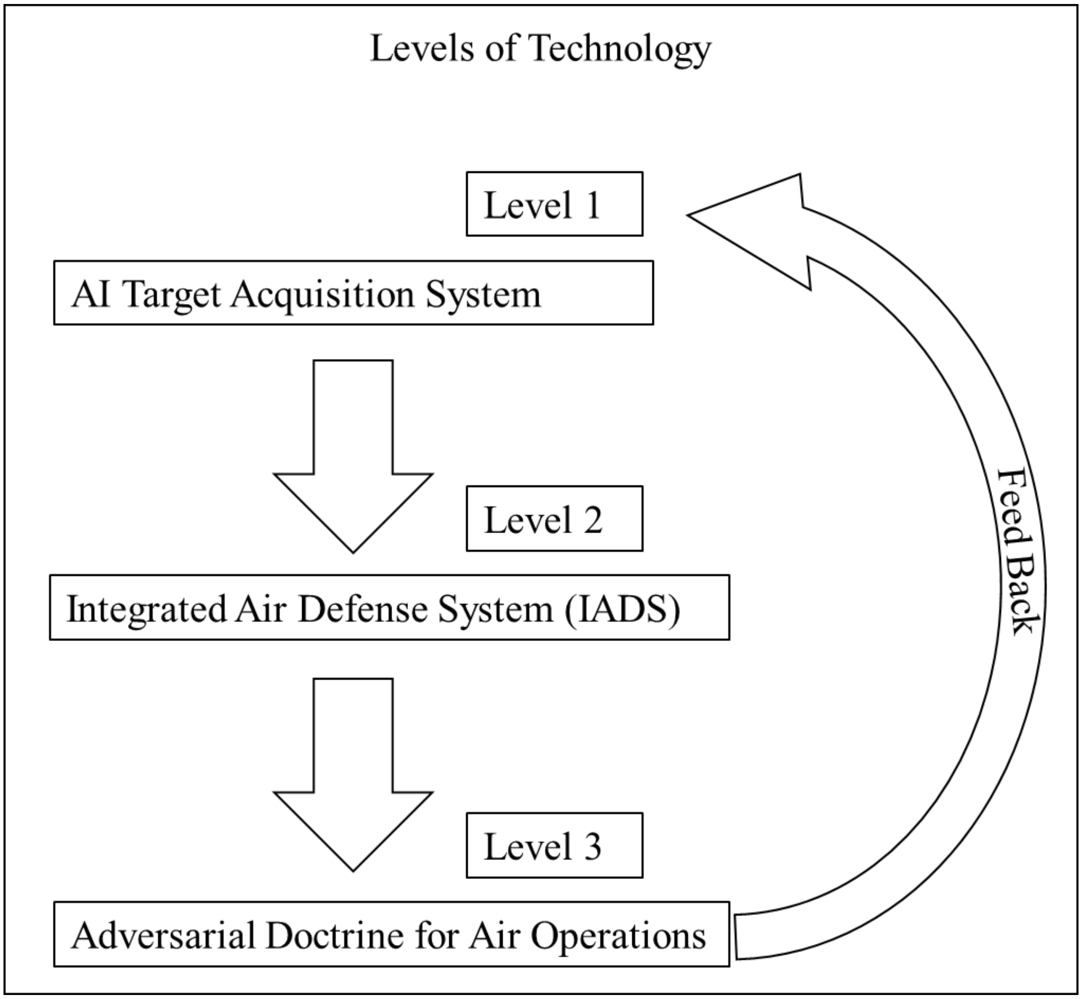

Figure 5. Allenby and Sarewitz's Levels of Technology. Braden Allenby, and Daniel Sarewitz, *The Techno-Human Condition* (Cambridge: MIT Press, 2011), 33-66.

Level 1 is the "immediate effectiveness of the technology itself as it is used" per the intended cause-and-effect.[90] An example of a Level 1 interaction is an air defense target acquisition system that uses an AI algorithm designed for pattern recognition. This algorithm learned from a large data set, characteristics of the target and non-target images. Level 1 is the

[90] Allenby and Sarewitz, 37.

target acquisition system's algorithm and other electro-mechanical systems functioning as designed and correctly identifying targets within its composite problem space.

Level 2 is when the technology becomes a part of a larger networked system. The larger systems include not only the hardware/software system but also the support infrastructure with the users and maintainers. For example, the Level 2 is when the target acquisition system becomes a part of a larger more complex integrated air defense system (IADS). The Level 2 has a complex problem space that includes the problem space of Level 1. The functionality of Level 2 is an emergent property of the larger system. The reason Level 2 functionality is an emergent property is that Level 2's overall performance is not predictable from Level 1 behavior.[91] How well an AI performs in target acquisition is not an indicator of the overall Level 2 IADS's performance. Level 1 does contribute to the overall performance of Level 2. It is impossible to predict Level 2 performance solely on that of Level 1.

Level 3, is an "Earth System – that is, a complex, constantly changing and adapting system in which human, built and natural elements interact," where the complexity is difficult to observe, comprehend and manage.[92] Understanding of Level 3 does not exist in any one discipline or intellectual framework. Level 3 develops as an aggregate of social constructions where the subjective reality and objective reality apply mutually recursive feedback. An example of Level 3 is when an IADS is part of a national defense system where the overall strategy of employment and the IADS effectiveness forces changes to adversarial aircraft doctrine, tactics, techniques, and procedures (TTP), and countermeasures. A change in enemy doctrine or TTP elicits changes in Level 1 technology through the application of new methods in AI for targeting algorithms or missile guidance systems.

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[91] Allenby and Sarewitz, 38.

[92] Allenby and Sarewitz, 63.

Innovations in one level will have a cascading effect that precipitate changes in the other levels.[93] System changes caused by advancements in technology at other levels are not reversible without large expenditures of energy. The changes across levels of interaction are difficult to anticipate rendering forecast for AI integration spurious. Extrapolation of AI capabilities from other levels are ripe for inflating expectations at the Earth system.

Artificial Intelligence Functional Framework

Current breakthroughs in AI are the results of research from 30 years ago. The first neural network appeared in 1950s called the Perceptron. In 1969, Minsky proved the Perception could calculate simple functions. In 1986, a cognitive psychologist, Geoffrey Hinton showed that a deep neural net is trainable. Not until 2012 did computational power arrive that could train the deep neural net for pattern recognition. Pattern recognition sparked a resurgence of interest in the future potential of a general AI. However, deep learning is a "thoughtless fuzzy pattern recognizer…they represent, at best, a limited brand of intelligence, one that is easily fooled."[94] Pattern recognition is very useful and deep learning provides a powerful tool for special purpose algorithms. However deep learning is not human level intelligence because real intelligence, "doesn't break when you slightly change the problem."[95]

Over two thousand years of philosophical tradition has envisioned the arrival of some human-made form of AI rivaling human intelligence. The historical belief and desire for a true AGI are vulnerable to overestimation of AI technology through the hype cycle. The AI functional framework (AIFF) provides a method to delineate the fungible boundaries between human and algorithm intelligence.

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[93] Allenby and Sarewitz, 39.

[94] James Somers, "Is AI Riding a One Trick Pony?" Intelligent Machines, MIT Technology Review, September 29, 2017, accessed April 9, 2018, https://www.technologyreview.com/s/608911/is-ai-riding-a-one-trick-pony/

[95] Somers.

The AIFF is a graphical representation of an algorithm's relationship respect to the OE. For AI to operate in the OE, it needs to characterize the task environment into formalized problem spaces. The characteristics of an AI's problem space will be at some point in the Cynefin quadrants: simple, complicated, complex or chaotic. The AI using the Cynefin quadrants problem space will function as Level 1 (purposely designed system), Level 2 (networked system of systems) and Level 3 (Earth system) technologies.

For example, an average automobile has an algorithm that controls the amount of fuel delivered to the engine. This algorithm receives input from the car's sensors; accelerator pedal, mass air flow, cam position, etc. The sensors' data allows the algorithm to quantify the OE and respond with the appropriate fuel quantity. The automobile fuel delivery algorithm is an example of an AI, Level 1, with a problem space in the ordered knowledge domain, shown in Figure 6. As the algorithm functions, part of a larger system of systems, Level 2, with the human driver and the road network the task environment grows in complexity but the AI problem space remains in the ordered knowledge domain. The fuel algorithm's problem space does not change when the task environment changes.

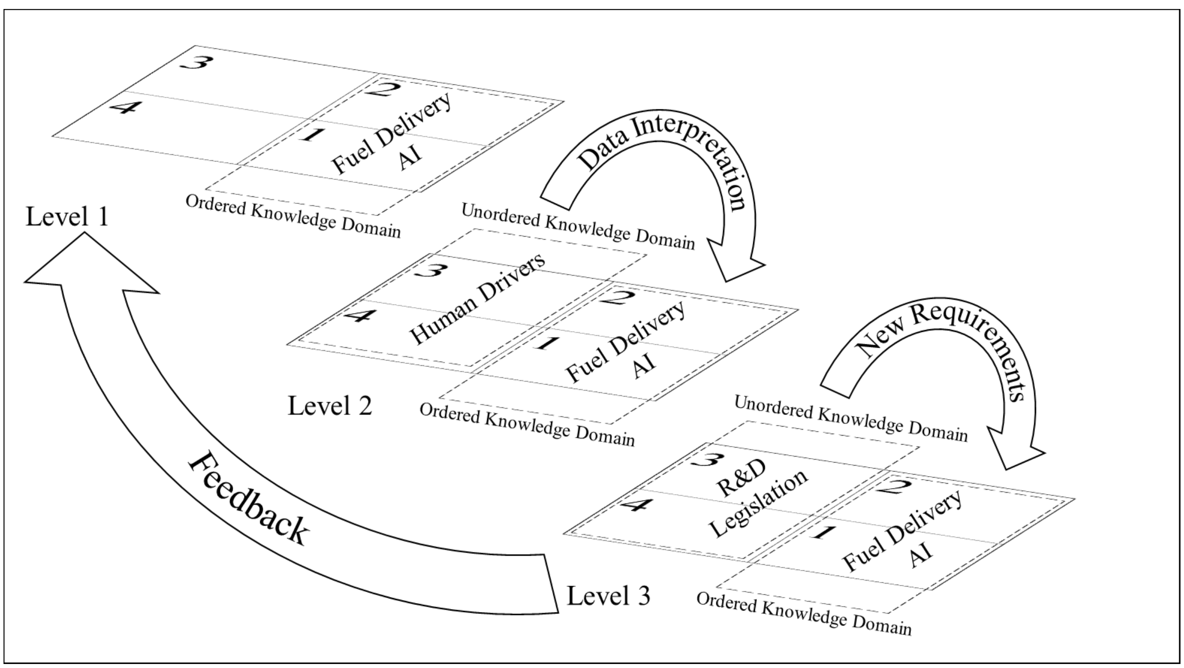

Figure 6. Artificial Intelligence Functional Framework (AIFF), Fuel Delivery Algorithm.

The algorithm is oblivious to the drivers desired objective of going from point A to point B. The human driver interprets the complexity of Level 2 into tasks solvable in the AI's simple problem space. The Level 3, Earth system, is beyond the Algorithm's comprehension through its problem space. For the AI to adapt to changes to Level 3, it requires additional systems of R&D and legislators to create and implement new fuel delivery requirements. The new requirements force changes to Level 1 technology. At Level 2 and 3, the AI has the relevant elements from the unordered knowledge domain translated into meaningful usable inputs.

The AIFF for a deep learning AI is more complicated than a simple fuel delivery algorithm. Deep learning methods use stochastic and heuristic algorithms to make an approximation of the complex and chaotic problem spaces. The AI approximations of complex problems spaces allow algorithms to remain in the ordered problem space and manage randomness and entropy. However, the chaotic problem space is incompatible with probabilistic algorithmic methods and require an intelligence capable of self-reference while dealing with incomplete information.

Deep learning is a purpose-built algorithm for a specific application that depends on the available data. Figure 7, is a graphic showing the AIFF for a deep leaning algorithm. At Level 1 an algorithm uses data from the unordered knowledge domain. The data is ingested through a complicated problem space to determine an appropriate algorithmic response. The algorithmic response that is learned in Level 1 is then applied to a specific application in a complex task environment at Level 2. Feedback from actions in Level 2 reinforces the deep leaning from Level 1. A deep learning AI developed for a specific application applied at Level 2 cannot change to a new application at Level 3 without feedback to Level 1. At Level 1 the AI will need a period of relearning for the new specific application.

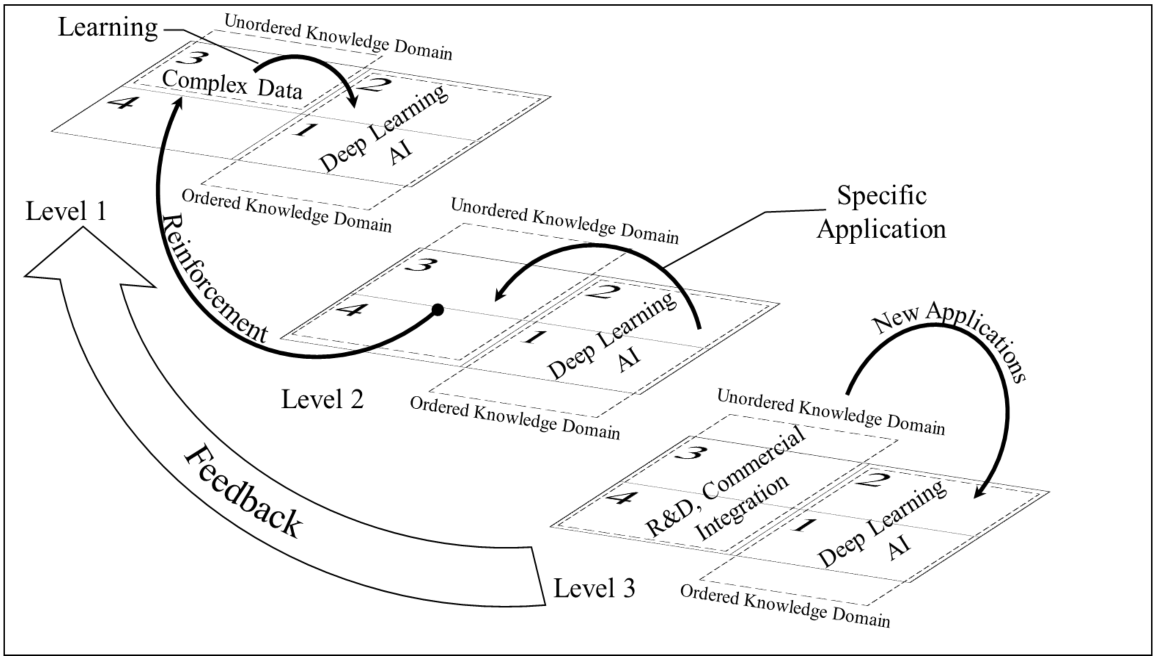

Figure 7. Artificial Intelligence Functional Framework (AIFF), Deep Learning Algorithm.

Deep learning algorithms reside in the ordered knowledge domain at Level 1. The AI has methods to bring complex data into the complicated domain without needing a complex problem space. The deep learning algorithm at Level 2 acts on the goals established and learned at Level 1. The framing, symbol and feature engineering problems currently prevent deep learning form picking the appropriate method for applying machine learning at Level 2. The problems for AI at Level 2 are exponentially more difficult at Level 3.

Pundits inflating the hype cycle using scenarios with independent AI operating at Level 3 drastically overestimate the trajectory of development. The hype cycle using "The Matrix" and "Ex Machina," as data points, place AI functioning in the chaotic quadrant at Level 3. [96] The current AI functioning in the complicated problem spaces in the ordered knowledge domains sets AI development on a low angle trajectory within the next twenty to thirty years. If the expectation

[96] Ryan Browne, "Elon Musk Warns A.I. Could Create an 'Immortal Dictator from which We Can Never Escape'," Tech, CNBC (April 2018), accessed April 10, 2018, https://www.cnbc.com/2018/04/06/elon-musk-warns-ai-could-create-immortal-dictator-in-documentary.html.

is for independent AGI at Level 3 problem spaces, the US will see a period of disillusionment which risks allowing peers with more realistic expectations to achieve AI technical dominance.

US Army future objectives

In 1989, the Logistics Management Institute authored "A Plan for the Application of Artificial Intelligence to DoD Logistics." In this report Jeffrey Melaragno and Mary Allen, Ph.D. suggested six AI technologies with the potential application: expert/knowledge-based systems, natural language, speech recognition, three-dimensional vision, intelligent robotics, and neural networks. They claimed that integration of AI would reduce cost, improve efficiency, and reduce the time for planning and mobilizing.[97]

Nearly thirty years later with improvements in neural networks and deep learning for pattern recognition, the US Army has issued new objectives for the integration of AI. The current focus on AI technologies as part the Army's strategy to maintain technical overmatch with adversaries. In 2014 the Army Capabilities Integration Center (ARCIC) released *The US Army Operating Concept: Win in a Complex World* (AOC). The AOC advocates for autonomous and semi-autonomous robotic systems with the ability to learn, aid in the decision-making process, and reduce the cognitive burdens of rapid decisions.[98] The US Army Research Laboratory, in 2015, published *Visualizing the Tactical Ground Battlefield in the Year 2050: Workshop Report* describing the battlefield of 2050. Per the report, a component of the future battlefield will be AI providing automated decision making and controlling autonomous processes. "Decision agents would be integral to all of the processes associated with" command and control, intelligence collection and processing. [99] The ARCIC released in 2017, TRADOC pamphlets covering The

[97] Jeffrey Melaragno and Mary Allen, *A Plan for the Application of Artificial Intelligence to DoD Logistics* (Bethesda: Logistics Management Institute, October 1989), v-vii.

[98] Army Training and Doctrine Command Pamphlet 525-3-1, *The US Army Operating Concept: Win in a Complex World 2020 – 2040* (Washington, DC: Government Printing Office, 2014), 40.

[99] Alexander Kott et al., *ARL-SR-0327 Visualizing the Tactical Ground Battlefield in the Year 2050: Workshop Report* (Adelphi, MD: US Army Research Laboratory, June 2015): 9.

Army Functional Concepts (AFC) for the warfighting functions of 2020 – 2040, each warfighting functions anticipates the broad incorporation of AI technologies to solve a host of challenges.[100] Each warfighting functions' functional concept includes some form of AI to aid in decision-making, control systems autonomously, and monitor the OE. Desire to integrate AI across warfighting functions will involve more than just developing purpose built algorithms.

Current efforts for adoption of AI come from the Algorithmic Warfare Cross-Function Team from the Office of the Undersecretary of Defense for Intelligence who launched Project Maven, 2017, an AI algorithm for extracting data from full motion video. This is an effort to use AI for greater efficiencies in imagery analysis by process millions of hours of video. Col. Drew Cukor, commenting on Project Maven's focus on using machine learning for pattern recognition, said, "We are in an AI arms race...No area will be left unaffected by the impact of this technology."[101] The pending success of Project Maven will impact how the DoD integrates AI across the enterprise.

Looking at Project Maven through the AIFF puts the Python scripted coded rules in the ordered domain problem spaces. It may use complex data but the AI is not functioning in a complex problem space. At Level 1, the algorithm looks for specific objects defined by users. The Level 2 interaction of the pilot program is the systems of systems that incorporates Google, other

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[100] TRADOC Pamphlet 525-2-1, The US Army Functional Concept for Intelligence 2020-2040 (Washington, DC: Government Printing Office, 2017), 24, 44-46; TRADOC Pamphlet 525-3-3, The US Army Functional Concept for Mission Command 2020-2040 (Washington, DC: Government Printing Office, 2017), 56; TRADOC Pamphlet 525-3-4, The US Army Functional Concept for Fires 2020-2040; 2017, 23, 25; TRADOC Pamphlet 525-3-5, The US Army Functional Concept for Maneuver Support 2020-2040 (Washington, DC: Government Printing Office, 2017), 13, 21, 24, 37-39; TRADOC Pamphlet 525-3-6, The US Army Functional Concept for Movement and Maneuver 2020-2040 (Washington, DC: Government Printing Office, 2017), 41; TRADOC Pamphlet 525-4-1, The US Army Functional Concept for Sustainment 2020-2040 (Washington, DC: Government Printing Office, 2017), 9, 15, 38; TRADOC Pamphlet 525-8-2, The US Army Functional Concept for Training and Education 2020-2040 (Washington, DC: Government Printing Office, 2017) 31, 32-38.

[101] Cheryl Pellerin, "Project Maven to Deploy Computer Algorithms to War Zone by Year's End," DoD News, Defense Media Activity, July 21, 2017, Accessed April 7, 2018, https://www.defense.gov/News/Article/Article/1254719/project-maven-to-deploy-computer-algorithms-to-war-zone-by-years-end.

government agencies, and the DoD. Where the developers and clients provide objectives and interpret the complexity into meaningful input for the algorithm to apply its deep learning for pattern recognition. The Level 3 involvement includes not only the developer and users but thousands in Silicon Valley's tech culture who object and protest the DoD use of AI in warfare.[102] The Level 3, ethical considerations articulated by the public, industry and US government will impact how AI functions at Level 2. Additionally, the ethical consideration will affect future development of the technology.

Machine learning has been in the Level 1 ordered domain for over thirty years. Recent methods using complex data for machine learning is not allowing algorithms to make the leap from ordered knowledge domain problem spaces to the unordered problem spaces. To progress towards unordered problem spaces require improvements in algorithmic planning, which is still extremely difficult. Without algorithmic planning, an AI will be incapable of autonomously navigating tactical situations. The weakness in planning in a complex problem space leaves algorithms not smart enough to be of any strategic advantage. Progress in machine learning may continue to advance but without domain-independent planning AI will limit military applications of AI.[103]

Realistic AI Capabilities

The current AI technology shows promise for semi-automated decision making and semi-autonomous control. For AI to contribute to successful problem solving across both ordered and unordered knowledge domains it will depend on more than the linear progression of technological advancement. There are still significant challenges in knowledge representation and algorithm development that will need new tools and hardware for processing. Researchers believed that for

[102] Scott Shane and Diasuke Wakabayashi, "The Business of War: Google Employees Protest Work for the Pentagon," *Technology, The New York Times*, April 4, 2018, accessed April 10, 2018, https://www.nytimes.com/2018/04/04/technology/google-letter-ceo-pentagon-project.html.

[103] Edward Geist, "(Automated) Planning for Tomorrow: Will Artificial Intelligence Get Smarter?" *Bulletin of the Atomic Scientist* 73, no. 2 (March 2017): 81.

an algorithm to achieve grandmaster chess playing ability it would need some form of general intelligence, with abstract thinking, flexible planning and modeling the other players' thinking. However, it turned out that a special purpose algorithm would work. Deep Blue, an AI chess engine beat chess master Garry Kasparov in 1997. Kasparov claimed to have seen a glimpse of intelligence in Deep Blues moves. The AI's ability to play grandmaster-level chess turned out to be a relatively simple algorithm. The simplicity of the algorithm left Deep Blue incapable of anything else but chess game play. The trend in AI development as seen in Deep Blue is to take complex task environments and translate them in to simple or complicated problem spaces. The simplification of task environments comes at a cost in creating a narrowly focused algorithms.

Google's AI, AlphaGo, won against a human Go champion in 2017. This win offered hope that machine learning will lead to general intelligence for AI. The game of Go is more challenging than chess requiring significant probability and decision making calculations; but just like Deep Blue, AlphaGo is a purpose-built algorithm. The game of Go is also at best no more than a complicated problem space of directed order. AI's use of inference algorithms is still costly regarding computational power. Machine learning algorithms need more R&D to move past the nascent stage of development. For AI to have autonomy in complex problem spaces, algorithms will need to create high-level actions from primitive ones automatically, learning new model structures. The capability of AI to autonomously create high-level actions from primitive ones is still an unknown quantity.[104]

The unpredictable and dynamic nature of the unordered domain will continue to present challenges for automated decision making and autonomous control algorithms. AI is a powerful tool for quickly processing information, once given a specific set of rules. AI systems function as designed based on their programming. Which in most cases AI trends to be "only as smart as the

[104] Stuart Russell, "Rationality and Intelligence: A Brief Update," *Fundamental Issues of Artificial Intelligence*, ed. V.C. Müller (Cham, Switzerland: Springer International Publishing, 2016), 20-22.

programmer who has written the programs in the first place."[105] AI researcher Francois Chollet at Google explains that the biggest problem for AI is abstraction and reasoning. He further describes that current learning algorithms require massive amounts of data, use direct pattern recognition, and are poor at planning.[106] AI functions on rules and probabilities which makes the algorithms fragile and ineffective outside of their designed problem space.[107]

Humans are capable of learning from a few instances, doing long-term planning, creating abstracts models of imaged problem spaces, and manipulating the models for broad generalizations. In contrast to humans, for a machine to learn, it needs an enormous amount of strictly labeled data annotated for specific objectives. Chollet explains that neural networks using statistical algorithms have impressive results generalizing with large data samples, but the same algorithms are inconsistent with individual cases "making mistakes humans would never make."[108] The results are highly dependent on the data and fall prey to 'garbage-in, garbage-out' scenarios.

Deep learning data dependency makes AI vulnerable to algorithmic bias. For example, automated decision-making (ADM) criminal justice algorithms used by state and local governments to assess the risk of criminal recidivism upon parole demonstrated algorithmic bias against minorities.[109] Mathematician Cathy O'Neil says, "people are often too willing to trust in mathematical models because they believe it will remove human bias…People trust them too

[105] Alexander Arnall, *Future Technology Today's Choices* (London: Greenpeace Environmental Trust, 2003), 42.

[106] Francois Chollet, "Advances in Deep Learning for Mathematical Theorem Proving" (keynote address at AI by The Bay, San Francisco, CA, March 6-8, 2017), accessed April 9, 2018, https://www.youtube.com/watch?v=UAa2o0W7vcg.

[107] Arnall, 42.

[108] Chollet, keynote address.

[109] Matthias Spielkamp, "Inspecting Algorithms for Bias," *Business Impact, MIT Technology Review*, July/August 2017 Issue, June 12, 2017, accessed April 9, 2018, https://www.technologyreview.com/s/607955/inspecting-algorithms-for-bias.

much."[110] ADM algorithms cannot determine on their own what rules to apply for any given task. Machine learning and deep learning will not make a general AI. Unlike human learning AI, learning is pattern recognition, classification, and extrapolation based on large datasets.[111] Success in deep learning is in directed order problem spaces. Deep learning methods in one problem space cannot scale to other problem spaces which would require general intelligence.[112]

Conclusion

General officers, field grade officers, and company grade officers each have different information requirements for decision making. AI has the potential to help but needs tailoring to their specific informational requirements. Those closest to the problem where AI can offer advantages need a method to understand the technology and determine its appropriateness. The AI functioning framework provides a method to visualize algorithmic capability. Understanding the general nature of AI provides a gauge to judge AI innovation and the accompanying hype cycle. The hype cycle has the ability to cause delays in developing functional solutions with AI.

David Pizarro, associate professor of psychology at Cornell University underscored that the "social and moral institutions – are ill-equipped to deal with the rapid pace of technological innovation."[113] The advent of the steam engine and the mass production of steel changed the physical landscape and led to the codification of intangible property rights and contract law. AI technology is permeating the technological landscape at an exponential rate and will impact most of modern society. As society integrates more expansive AI with interconnected systems there will be compounding affects creating increased complexity along with a demand for people who

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[110] Cathy O'Neil, "When Not to Trust the Algorithm," Analytics, Harvard Business Review, October, 6, 2016, accessed April 9, 2018, https://hbr.org/ideacast/2016/10/when-not-to-trust-the-algorithm.

[111] Yusuke Sugomori, et al., *Deep Learning: Practical Neural Networks with Java,* (Birmingham: Packt Publishing Limited, 2017), epub.

[112] Chollet, keynote address.

[113] David Pizarro, "The Stifling of Technological Progress," *What Should We Be Worried About? Real Scenarios That Keep Scientists Up at Night*, ed. John Brockman (New York: Harper Collins Publishers, 2014), 39.

can operate in the new complex environment. The current societal infrastructure will need to evolve to support a knowledge industry of researchers, developers, maintainers and knowledgable users.

The current state of AI as technology has significant challenges to overcome before it meets the US Army's desire for future integration of AI. The current AI technologies are not scalable form ordered to unordered knowledge domain problem spaces. New methods and technologies will need to be invented and refined before achieving true human-like AGI. Additional technical issues that need resolution:

- Reduce the need for massive data sets.
- Have a natural way of managing hierarchical structures.
- Have an efficient method for open-ended inference.
- Have neural networks be open for verification and validation.
- Manage and incorporate prior knowledge from other agents.
- Delineate between correlation and causation.
- Have dynamic rules to address complex problem spaces.
- Be trustworthy with the probabilistic output.
- Be manufacturable and serviceable.[114]

The Department of Defense (DoD), as well as the Army, are looking at future technology to mitigate future adversarial asymmetric capabilities. AI as a technology has a history of big promises and overselling progress. US security should focus on identifying future problems and work to create solutions to those problems instead of focusing on technology with the expectation that technological advances will solve future asymmetrical threats. AI surely will in some cases offer solutions to these future threats, but in many cases, the level 3 interactions with the Earth systems will produce unintended consequences that may be worse than the initial problem.

The US Army needs to avoid falling prey to the cycle of hyperbole. Previous iterations of AI development give way to developers overpromising future capabilities of AI which was then followed by years of technological abandonment. The military cannot afford to have inflated

[114] Gary Marcus, "Deep Learning: A Critical Appraisal," ARXIV Cornell University, January 2, 2018, accessed April 21, 2018, https://arxiv.org/abs/1801.00631

expectations that precipitate a period of disillusionment ceding initiative and technological advantage peer and near peer competitors like Russia and China who are pursuing weaponized AI. Leaders and decision makers need a realistic understanding of AI development to guide them in their integration of AI into the Army enterprise.

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