AFRL-AFOSR-VA-TR-2019-0243

Ideas Lab for Imagining Artificial Intelligence and Augmented Cognition in the USAF of 2030

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08/22/2019
Final Report

DISTRIBUTION A: Distribution approved for public release.

Air Force Research Laboratory
AF Office Of Scientific Research (AFOSR)/ RTB2
Arlington, Virginia 22203
Air Force Materiel Command

REPORT DOCUMENTATION PAGE

Form Approved OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*
22-08-2019

2. REPORT TYPE
Final Performance

3. DATES COVERED *(From - To)*
01 Mar 2018 to 30 Jun 2019

4. TITLE AND SUBTITLE
Ideas Lab for Imagining Artificial Intelligence and Augmented Cognition in the USAF of 2030

5a. CONTRACT NUMBER

5b. GRANT NUMBER
FA9550-18-1-0301

5c. PROGRAM ELEMENT NUMBER
61102F

6. AUTHOR(S)
James Olds

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
GEORGE MASON UNIVERSITY
4400 UNIVERSITY DR
FAIRFAX, VA 22030-4422 US

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
AF Office of Scientific Research
875 N. Randolph St. Room 3112
Arlington, VA 22203

10. SPONSOR/MONITOR'S ACRONYM(S)
AFRL/AFOSR RTB2

11. SPONSOR/MONITOR'S REPORT NUMBER(S)
AFRL-AFOSR-VA-TR-2019-0243

12. DISTRIBUTION/AVAILABILITY STATEMENT
A DISTRIBUTION UNLIMITED: PB Public Release

13. SUPPLEMENTARY NOTES

14. ABSTRACT
In this final report, we cover the period from the beginning of this project in March of 2018 until June of 2019. This period includes a no-cost extension of the project which was granted in September of 2019. The aim of the project is to explore the mid-term (10+ years) future of Artificial Intelligence and Augmented Cognition (AI) in the context of the future USAF, and to create a novel networked community of innovation and to prepare a formal report on the topic for the USAF. We convened an Ideas Lab for Imagining Artificial Intelligence and Augmented Cognition in the USAF of 2030. GMU partnered with professional facilitators from Knowinnovation (KI) to design, plan, prepare and facilitate a 5-day workshop.
The primary objective of the effort is to illuminate the 2030 technology horizon for AI in the USAF context. A secondary objective is to facilitate the building of a community of USAF aligned experts who can provide continuing advice to the USAF as an external advisory board (akin to the Jasons). The final objective is to facilitate the discussions necessary to build a pipeline of technological expertise in AI to avoid or respond to strategic surprise in this area.
The primary impact of the effort will be to catalyze advanced situational awareness about putative developments in AI over the next decade and a half within the context of USAF requirements and coincides with USAF Secretary Heather Wilson's renewed emphasis on electronic warfare, networked capabilities, and control of the electromagnetic spectrum.

15. SUBJECT TERMS
SecAF 2030

16. SECURITY CLASSIFICATION OF:

17. LIMITATION OF ABSTRACT

18. NUMBER OF

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

a. REPORT	b. ABSTRACT	c. THIS PAGE		PAGES	19a. NAME OF RESPONSIBLE PERSON
Unclassified	Unclassified	Unclassified	UU		BLACKWOOD, MILTON
					19b. TELEPHONE NUMBER *(Include area code)* 703-588-8618

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

DISTRIBUTION A: Distribution approved for public release.

2019

THE AI ACCELERATION: IMPLICATIONS FOR THE US AIR FORCE OF 2030

James L. Olds

USAF 2030 REPORT

6/19/2019

Acknowledgement:

This report represents the product of many scientists from diverse disciplines. Beyond the authors named, all the participants in the online components of the project played critical roles. The facilitation role of Know Innovation Inc. was also central to the project. In particular, Andy Burnett, Stavros Michailidis, and Donnalyn Roxey all were critical to project completion. Sara Bradley was essential to the logistical success of the Ideas Lab. Finally, the arduous work of Muhammad Salar Khan was fundamental to the integration of so many differing inputs.

USAF 2030 REPORT

June 2019

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1. Executive Summary

"We will listen broadly and engage those who are on the cutting edge of science so that we can focus our research efforts on the pathways that are vital to our future as a service." USAF Secretary Dr. Heather Wilson, September 18, 2017

Artificial Intelligence and Augmented Cognition (AI; to encompass both) already guide critical United States Air Force (USAF) functions. By 2030, AI will permeate the mission space of the service. As the USAF clearly states, what is critical for the science of the USAF, "the future does not invent itself." In line with this, the goal of this report is to help envision and guide the invention of the future of AI for the USAF. What is needed, then, is R&D that takes full advantage of, and pushes the boundaries in, AI and how it can elevate USAF capacity to protect our nation across all its mission domains.

A rich history of USAF technologies dates back decades (e.g., McCulloch & Pitts, 1943; Rosenblatt, 1958; Rummelhart et al., 1985; Hopfield, 1988), but, with advances in computational power, many have rapidly evolved (LeCun et al., 1998; Hassabis et al., 2017) in such a way that they are, or soon will be, ubiquitous in the warfighting environment. They are likely to become central to the armamentarium of the USAF in 2030. From autonomous drones to human wearables, smart machines and their interfaces with humans are approaching the tipping point for revolutionizing the warfighting environment of our nation's Air Force personnel. We term this recent trend: *The AI Acceleration*.

What is critical to recognize is that the United States is not necessarily leading in all the associated technologies. This represents a significant vulnerability and a gap to overcome. The AI Acceleration has not escaped the notice of our adversaries and allies alike. For example, Russian President Vladimir Putin has noted that "whoever becomes the leader in this sphere will become the ruler of the world." (CNN, Sept. 2, 2017). French President Emmanuel Macron has committed his country to major new investments to "finance research in…Artificial Intelligence" (Rabesandratana, 2018). In China, AI R&D is carefully nurtured, all while that country institutes progressively restrictive curbs on transfers of scientific data by foreign businesses (Ding, 2018). President Xi JinPing said: "We need to speed up building China into a strong country with advanced manufacturing, pushing for deep integration between the real economy and advanced technologies including internet, big data, and artificial intelligence." (Reuters, Oct. 18, 2017).

To address this gap, over 100 leading academic, industry and government scientists contributed to this study highlighting how 'The AI Acceleration' may shape the USAF of 2030. These experts convened online and, with a subset, face-to-face (this report's authors) during the second quarter of 2018 in an "NSF Ideas Lab" format facilitated by Knowinnovation (KI), a group that has extensive experience facilitating innovative and interdisciplinary scientific advancement through both face-to-face and virtual interactions.[1]

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[1] The Ideas Lab methodology used here has consistently produced successful results in advancing transdisciplinary scientific innovation. KI pioneered its methodology in 2003 in partnership with the EPSRC (Engineering and Physical Sciences Research Council) in the UK. The EPSRC workshops, known as Sandpits, were eventually adopted and

This report represents the integration of the ideas generated through these interdisciplinary interactions and focuses on three key areas: machines, human-machine, and human, within the context of the USAF and its warfighters. Below we operationally define these terms and we illustrate them in Figure 1 (p.16).

- **Machines:**

The need to develop machines and algorithms that can operate autonomously, with reduced risk, and side-by-side with human personnel, and over the long-term in the extreme environments of air and space, is clear. Machines will replace and, in some cases, transform current capacities. In order to prepare for potential paradigm shifting disruptions due to the rapidly evolving, highly dynamic cyberspace, the USAF needs to adopt a proactive stance that includes a continual spiral development of new systems informed by research investments from both government and the private sector. Experts agreed that changes would not occur along existing trend lines. Cyberspace is rapidly evolving such that the highly dynamic environment and rapid changes will most likely disrupt expectations. There was a consensus that it is critical to invest in research to develop systems that are adaptable, flexible, robust, safe to use and secure from threats and to assess which ones are critical to being sourced in the United States.

- **Human-Machine:**

In the 2030 horizon, and with careful leadership into an AI-accelerated mutation of its organizational structure, USAF has the potential to realize the transformational enhancements of human-machine teaming that will result in substantial gains in warfighter cognition and collaboration including, but not limited to, situational awareness, decision speed, operational and organizational agility. This will include the early adoption of advanced human-machine and brain-computer interfaces; the pervasive integration of wearable, micro- and nano-electronic sensors for physio-, psycho- and neuro-monitoring, feedback and closed-loop real-time intervention that will be connected with specific machines or broader command systems, especially valuable in extreme environments; an integration of teamwork between human and informational or robotic machines; the creation of virtual worlds mapping cyber-spaces and allowing human deployment in a spatially and informationally intuitive manner; and the mundane interactions with expert digital assistants, cloud-connected information systems with natural language processing capabilities that significantly shorten the distance between human and the information they operationally need. Across these topics, there was a consensus about several broad themes to human-machine teaming.

I) Human Machine fusion to enhance individual performance: this area suggests emerging technologies to enhance human performance, including cognition, behavior, and health.

II) Human-Machine teaming: this area points to emerging paradigms for the collaborative work of hybrid teams of human and machine.

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adapted by the US National Science Foundation and are now known as an Ideas Lab (https://www.nsf.gov/pubs/policydocs/pappguide/nsf16001/nsf16_1.pdf#page=54). The NSF have also championed using Ideas Labs in other areas of government including the National Institutes of Health, National Aeronautics and Space Administration, National Academies Science Engineering Medicine, and the National Labs.

III) System-wide monitoring of collaborative Human-Machine performance: this area stresses the importance of a careful, continuous and dynamic oversight of those novel technologies.

- **Humans:**

The group agreed that human agents are integral components to success across all areas of the USAF's mission. By 2030, humans will interact with artificial intelligence as a matter of course in all USAF operations, from logistics to maintaining or controlling warfighting machines. Moreover, there will be a significant number of airmen Air Force personnel who will perform their duties in an enhanced cognition mode enabled by advances in neurotechnologies. The AI acceleration will undoubtedly shape the workforce of the future. Given the rapid evolution of the operational environment, the group focused on the fact that attributes of the service officer that are desirable in 2030 may be very different from those that were valued in the 20th century.

It was agreed that it is essential to build an understanding of how to train and nurture the current and next generation of Air Force personnel in the development and adoption of AI-accelerated technology. This requires system-level integration of, and interaction between, service personnel and the R&D and acquisitions community. For example, efficacious adoption can be done, in part, by involving service personnel in the design of AI systems. After recruitment, Air Force personnel must be trained in the relevant skills to tackle the challenges of the future USAF. Therefore, understanding how to improve and maintain human performance, such as stamina, peak cognition, staying on task, etc., in this AI infused operational environment is crucial in preparing for 2030 operations.

- **Cross-cutting issues:**

The group identified many cross-cutting critical issues. These included strategic surprise, ethical, legal, social and energy challenges for the USAF. In the case of strategic surprise, the scope of the challenge for this report was limited to technological advances in AI that can be anticipated as emerging from our adversaries. In the case of ethical, legal and social issues, there was an explicit recognition that constraints voluntarily adopted by the USAF might very well not be limits for other nations. Finally, it was the consensus that energy availability and "quality" may represent a significant constraint for AI advances, particularly in the dynamic and remote environments that the USAF will have to operate in.

- **Recommendations:**

The USAF should coordinate its R&D investments in the AI Acceleration with other federal science agencies such as the NSF in addition to other parts of the DOD and the IC.

The USAF should scan R&D investments globally to gain insights into foreign government plans and capabilities that may represent warfighting challenges of the future.

The USAF should organize an AI Acceleration Advisory Committee of top-flight researchers from academia and industry to provide USAF leadership information and advice as the various disciplines underlying the science continue to advance.

The USAF should scaffold solutions by building platform technologies, data architecture, algorithms, and integration capabilities that serve to underpin AI applications.

The USAF should create the position of executive data architect to oversee the integration of AI, and the collection and securitization of centralized information resources from equipment to logistics and to human assets.

Conclusion:

The AI Acceleration will shape the readiness posture of the United States Air Force (USAF) in 2030. The consensus of the group was that the Air Force should accelerate development and acquisition of a *family of systems* in computational and neurotechnologies that will allow for profound advances in Command, Control, Communications, Computers, and Intelligence (C4I) across the entire spectrum of relevant warfighting environments. This family of systems falls into three areas: 1) catching up to existing commercial technologies (adoption), 2) core investment in the most relevant technological breakthroughs (e.g., AI) and 3) peripheral investment in those technologies that will fill the gaps left by the prominence of the former (e.g. quantum computing).

Such a future USAF will need machine, human-machine, and human interfaces that can offload or amplify human performance. This encompasses not only intent, but also the capability to respond to feedback from sensor streams, even under the extreme conditions produced by high-level combat environments. The entire AI ecosystem will need to provide for true autonomous operations of drones and agents (including swarms) operating in domains both familiar to, and heretofore not experienced by the USAF. This includes no longer just the atmosphere, but also “inner space” (i.e., the cyber-domain), and more critically, even higher levels of the atmosphere as well as low-earth orbit and deep space. Further, requires dealing with the concomitant energy constraints of those environments. Finally, this system of systems will need to have sufficient defense capabilities (perhaps bio-inspired) against peer competitors that are robust to degradation and attack.

Success for the USAF in the 2030 military context will depend not only on the AI Acceleration, but also upon the agility of command and control to respond to strategic surprise. Such a tipping point might occur in space technology (e.g., Space Elevator) but might also emerge disruptive developments in AI. For example, successful development and implementation of a *“General AI”* (defined as an AI able to do human-level cognition for any intellectual task) in the hands of a national peer competitor would put the USAF at a significant disadvantage. The military offset for such an advance will depend upon the USAF having a continuing awareness of the technology horizon--not only in aerospace but also at the intersection of cognition and computation as it applies to AI.

Author Biographies (face-to-face individuals)

Andreas G. Andreou (John Hopkins University): Andreas G. Andreou received his Ph.D. in electrical engineering and computer science in 1986 from Johns Hopkins University. Between 1986 and 1989 he held post-doctoral fellow and associate research scientist positions in the Electrical and Computer engineering department while also a member of the professional staff at the Johns Hopkins Applied Physics Laboratory. Andreou became an assistant professor of Electrical and Computer engineering in 1989, associate professor in 1993 and professor in 1996. He is also a professor of Computer Science and the Whitaker Biomedical Engineering Institute and director of the Institute's Fabrication and Lithography Facility in Clark Hall. He is the co-founder of the Johns Hopkins University Center for Language and Speech Processing. Between 2001 and 2003 he was the founding director of the ABET-accredited undergraduate Computer Engineering program. In 1996 and 1997 he was a visiting professor of the computation and neural systems program at the California Institute of Technology. In 1989 and 1991 he was awarded the R.W. Hart Prize for his work on mixed analog/digital integrated circuits for space applications. He is the recipient of the 1995 and 1997 Myril B. Reed Best Paper Award and the 2000 IEEE Circuits and Systems Society, Darlington Best Paper Award. During the summer of 2001, he was a visiting professor in the department of systems engineering and machine intelligence at Tohoku University. In 2006, Prof. Andreou was elected as an IEEE Fellow for his contribution to energy-efficient sensory microsystems.

Andreou's research interests include sensors, micropower electronics, heterogeneous microsystems, and information processing in biological systems. He is a co-editor of the IEEE Press book: Low-Voltage/Low-Power Integrated Circuits and Systems, 1998 (translated in Japanese) and the Kluwer Academic Publishers book: Adaptive Resonance Theory Microchips, 1998.

Monique Beaudoin (Johns Hopkins University Applied Physics Laboratory (JHU/APL): Monique Beaudoin, Ph.D., is the Neurological Health and Human Performance (NHHP) Program Manager at JHU/APL. As a PM, she manages neuroscience and performance-related research projects funded by Department of Defense (DoD) and US Government science and technology funding agencies, including two projects in support of the BRAIN Initiative. Before joining JHU/APL, Monique worked as an Associate Director/Science Director for the US Office of Naval Research (ONR) Global. As a government employee with the Navy, she served as a member of the US Army Research Office (ARO) Board of Visitors (BOV) and participated in numerous research program evaluation panels across the DoD services. Prior to that, she supported several governmental program managers as a Science and Engineering Technical Assistant (SETA) with Strategic Analysis, Inc. She holds a PhD in Neuroscience from the University of Colorado Anschutz Medical Campus and a BA in Psychology from the University of Massachusetts, Amherst.

Son K. Dao (HRL Laboratories): Son K. Dao, Director of Information & Systems Sciences at HRL Laboratories. He provides leadership and strategic vision/ideas for major researches areas in Human-Machine Collaboration, Computational Network Intelligence, Secure & Resilient Systems, and Autonomy Computing. He was co-founder and Chief Scientist of X-Labs, an Internet incubator, with a portfolio including Video Processing, Sport Augmented Reality, and Secure Broadband Network Protocols. He served as program committee member for many data and knowledge management, mobile and wireless networking, neural computational, and secure systems conferences and workshops. He was also a visiting professor at California State Uni. Northridge for 13 years and has developed two advanced computer science extension courses for UCLA and taught at UCLA for 9 years. He is on the advisory board for UCR school of Engineering and Computer Science. He served as a reviewer for NSF programs and Defense Sciences Board. He has about 40 publications and about 20 patents.

Stephen M. Fiore (University of Central Florida): Dr. Stephen M. Fiore is Director, Cognitive Sciences Laboratory, and Professor with the University of Central Florida's Cognitive Sciences Program in the Department of Philosophy and Institute for Simulation & Training. Dr. Fiore is Past-President of the Interdisciplinary Network for Group Research and a founding committee member for the annual Science of Team Science Conference. He maintains a multidisciplinary research interest that incorporates aspects of the cognitive, social, organizational, and computational sciences in the investigation of learning and performance in individuals and teams. His primary area of research is the interdisciplinary study of complex collaborative cognition and the understanding of how humans interact socially and with technology. Dr. Fiore has been a visiting scholar for the study of shared and extended cognition at École Normale Supérieure de Lyon in Lyon, France (2010) and he was a member of the expert panel for the Organisation for Economic Co-operation and Development's 2015 Programme for International Student Assessment (PISA) which focused on collaborative problem-solving skills. He has contributed to working groups for the National Academies of Science in understanding and measuring "21st Century Skills" and was a committee member of their "Science of Team Science" consensus study. As Principal Investigator and Co-Principal Investigator, he has helped to secure and manage approximately $25 million in research funding. He is co-author of a book on “Accelerating Expertise” (2013) and is a co-editor of volumes on Shared Cognition (2012), Macrocognition in Teams (2008), Distributed

Training (2007), and Team Cognition (2004). Dr. Fiore has also co-authored over 200 scholarly publications in the area of learning, memory, and problem solving on individuals and groups.

Chris Forsythe (Brain Hackers Association): Chris Forsythe is retired from Sandia National Laboratories where he spent 23 years conducting research and development focused on human performance. He now runs a non-profit that provides youth STEM programs. In this capacity, he has tried to focus on areas that have received little attention in STEM such as brain science, machine learning, AI and the importance of developing meta-cognitive skills. In a typical week, three to four days he will be at a school somewhere running activities with kids.

Jonathan Gratch (University of Southern California, Institute for Creative Technologies): Dr. Gratch is a Full Research Professor of Computer Science and Psychology at the University of Southern California (USC) and Director for Virtual Human Research at USC's Institute for Creative Technologies. He completed his Ph.D. in Computer Science at the University of Illinois in Urban-Champaign in 1995. Dr. Gratch's research focuses on computational models of human cognitive and social processes, especially emotion, and explores these models' role in shaping human-computer interactions in virtual environments. He studies the relationship between cognition and emotion, the cognitive processes underlying emotional responses, and the influence of emotion on decision making and physical behavior. He is the founding Editor-in-Chief of IEEE's *Transactions on Affective Computing*, Associate Editor of *Emotion Review* and the *Journal of Autonomous Agents and Multiagent Systems,* and former President of the Association for the Advancement of Affective Computing. He is an AAAI Fellow, a Cognitive Science Fellow, and SIGART Autonomous Agent's Award recipient.

Kara Hall (US National Cancer Institute, National Institutes of Health): Dr. Kara L. Hall is Director of the Science of Team Science (SciTS) and Theories Initiative at the US National Institutes of Health. Dr. Hall helped launch and build the SciTS field through her leadership conducting empirical studies, developing conceptual frameworks, creating practical strategies and resources (e.g., Team Science Toolkit), editing several special journal issues, serving as Chair or Co-chair of the Annual International SciTS Conferences (2014-2017), participating on External Advisory Boards for large (~$30mil) science initiatives, and delivering keynotes to stakeholders throughout the scientific enterprise. Her work aims to build an evidence base for effective team science approaches and support the translation of emerging knowledge into policies and practices. Notably, she served as a member of The National Academies Committee on the Science of Team Science (2012-15); in 2018 the resulting report *Enhancing the Effectiveness* of Team Science was listed in the top 30 most downloaded National Academies Press reports out of the more than 9000 released online since 1995. Dr. Hall is editor of the forthcoming book from Springer Publishing Company: *Strategies for Team Science Success: Handbook of Evidence-based Principles for Cross-disciplinary Science and Practical Lessons Learned from Health Researchers*. Dr. Hall also serves to advance dissemination and implementation science, the use, testing, and development of health behavior theory in cancer control research, systems science approaches, and teams/groups in health and healthcare. Dr. Hall earned her Masters and Doctoral degrees at the University of Rhode Island (URI) in Psychology with specializations in clinical psychology, neuropsychology, and behavioral science.

David J. Hamilton (Northrop Grumman Corporation): Dr. David J. Hamilton received his Neuroscience Ph.D. from George Mason University (GMU) in 2016. His dissertation research focused on defining morphologically defined hippocampal neuron types to facilitate biologically realistic computational modeling. David has extensive R&D experience in AI, ANNs, & ML applied to Defense & Finance. Specific projects include Intelligence Community analytic automation, Cyber Threat Analysis Platform R&D, US Treasury cyber defense, credit card fraud detection, Mult*INT fusion/analysis, LIDAR signal characterization, and passive/active sonar signal detection/classification. Companies include Northrop Grumman (2004-present), CardSystems/NeuralTech (1994-2004), Raytheon (1980-1994), and AAI (1977-1980). Earlier in his career, David received his MSEE from Loyola College, Maryland, and his BSEE from PSU. He is well published, holds memberships in Society for Neuroscience, AAAS, IEEE, and continues to maintain his association with GMU as an Affiliate Faculty.

Ilana Heintz (Raytheon BBN Technologies): Dr. Ilana Heintz is a Senior Scientist and Deputy Business Unit Manager at Raytheon BBN Technologies, where she leads the text processing group on multiple language-understanding research programs. Recent programs have focused on merging information from multiple data sources and domains (text, images, video), applying natural language processing to cyber security applications, and understanding causality and other relationships between events as expressed in text. Ilana also leads machine learning and artificial intelligence initiatives at BBN, including the application of machine learning in domains as diverse as RF emitter identification, sonar ship classification, and malware identification.

Todd Hylton (UC San Diego) Dr. Todd Hylton is the Executive Director of the Contextual Robotics Institute and Professor of Practice in the Electrical and Computer Engineering Department at UC San Diego. His research interests include novel computing systems and their application to the autonomous vehicle and robotic systems. Before his appointment at UC San Diego, he was Executive Vice President of Strategy and Research at Brain

Corporation, a San Diego-based robotics startup. From 2007 to 2012, Dr. Hylton served as a Program Manager at DARPA where he started and managed several projects including the Nano Air Vehicle program, the SyNAPSE program, and the Physical Intelligence program. Prior to DARPA, he ran a nanotechnology research group at SAIC, co-founded 4Wave, a specialty semiconductor equipment business, and served as CTO of Commonwealth Scientific Corporation. Dr. Hylton received his Ph.D. in Applied Physics from Stanford University in 1991 and his B.S. in Physics from M.I.T. in 1983.

Nadine Kabbani (George Mason University) Nadine Kabbani (Ph.D.) is an Associate Professor of Systems Biology and the Associate Director of the Interdisciplinary Program in Neuroscience at George Mason University. Her research focuses on the molecular mechanisms of regeneration and synaptic growth in the nervous system. She is the recipient of the American Association for the Advancement of Science (AAAS) 2018-2019 Science & Technology Policy Fellowship. Dr. Kabbani obtained her doctorate in Pharmacology from Penn State College of Medicine and her postdoctoral neuroscience training at Yale University and the Institut Pasteur in France.

Muhammad Salar Khan (George Mason University): Salar earned a master's degree in Public Policy as a Fulbright scholar at Oregon State University. Now, he is a Ph.D. Public Policy student and graduate research assistant at Schar School of Policy & Government, George Mason University. His interests are interdisciplinary, lying at the intersection of energy issues, economic policy, and science & technology policy. Beside teaching and graduate research assistant positions in graduate schools, he has worked with several organizations including the British Council, the Parliament of Pakistan, and the World Bank.

Asimina Kiourti (Ohio State University): **Asimina Kiourti** joined The Ohio State University (OSU) as an Assistant Professor of Electrical and Computer Engineering in Fall 2016. From 2013 to 2016 she served as a Post-Doctoral Researcher and then a Senior Research Associate at the OSU ElectroScience Laboratory. Before that, she received the Ph.D. degree in Electrical and Computer Engineering from the National Technical University of Athens, Greece (2013) and the M.Sc. degree from University College London, UK (2009). Prof. Kiourti's research interests include wearable and implantable sensors, antennas and electromagnetics for body area applications, and flexible textile-based electronics. Her publication record includes 8 book chapters, 6 patents, 39 journal papers, and over 85 conference papers. Her work has been recognized with over 40 scholarly awards, among which, the 2018 URSI Young Scientist Award, the 2014 IEEE EMB-S BRAIN Young Investigator Award, the 2013 Chorafas Foundation Outstanding Ph.D. Dissertation Award, the 2012 IEEE MTT-S Graduate Fellowship for Medical Applications, and the 2011 IEEE AP-S Doctoral Research Award. Prof. Kiourti's research has gained an international reputation and has been featured by TechCrunch, Gizmodo, Times of India, Australia Network News, and the ALN Magazine.

Jeff Krichmar (University of California, Irvine): Jeffrey L. Krichmar received a B.S. in Computer Science in 1983 from the University of Massachusetts at Amherst, an M.S. in Computer Science from The George Washington University in 1991, and a Ph.D. in Computational Sciences and Informatics from George Mason University in 1997. He spent 15 years as a software engineer on projects ranging from the PATRIOT Missile System at the Raytheon Corporation to Air Traffic Control for the Federal Systems Division of IBM. In 1997, he became an assistant professor at The Krasnow Institute for Advanced Study at George Mason University. From 1999 to 2007, he was a Senior Fellow in Theoretical Neurobiology at The Neurosciences Institute. He currently is a professor in the Department of Cognitive Sciences and the Department of Computer Science at the University of California, Irvine. His research interests include neurorobotics, embodied cognition, biologically plausible models of learning and memory, and the effect of neural architecture on neural function.

Amy A. Kruse (Platypus Institute): Dr. Amy Kruse is the Chief Scientific Officer of the Platypus Institute, an applied neuroscience research organization that translates cutting-edge neuroscience discoveries into practical tools and programs which enhance the human experience. Dr. Kruse's primary focus at the Institute is a project entitled "Human 2.0" – a multi-faceted initiative that helps selected individuals and teams leverage neurotechnology to generate meaningful competitive advantages. Her goal with the Human 2.0 project is to create a vibrant, widespread neurotechnology industry that allows humanity to upgrade the human brain and, thereby, the human condition.

Before joining the Platypus Institute, Dr. Kruse served as the Vice President and Chief Technology Officer of Cubic Global Defense, where she oversaw the company's research and development (R&D) programs. Prior to her work at Cubic, Dr. Kruse served as a government civilian program manager at the Defense Advanced Research Projects Agency (DARPA), where she created and oversaw the Agency's first performance-oriented neuroscience program. Her efforts at DARPA generated scientific breakthroughs in areas including augmented cognition, accelerated learning, cognitive enhancement, team neurodynamics, and brain stimulation, and they resulted in the creation of multiple programs that measurably enhanced both individual and team performance in several branches of the US military.

Amy is a member of several defense panels and advisory boards for organizations including the National Academies and the Defense Science Board. She is also the author of numerous scientific papers, chapters, and articles. Dr. Kruse earned a Bachelor of Science in Cell and Structural Biology and a PhD in Neuroscience from the University of Illinois at Champaign-Urbana, where she was awarded a National Science Foundation Graduate Fellowship.

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Contents

1. Introduction & Background

The United States in general, and its Air Force (hereinafter, "USAF"), in particular, maintained operational superiority throughout the 20th century because it was continually at the forefront of developing technologies. We submit that the USAF cannot afford to ignore the significance of the emerging Artificial Intelligence (AI) interventions. As the understanding of AI matures, its uses and applications will become universal and ubiquitous providing both significant opportunities and threats to national security. Presently, the full range of benefits from AI, including—pattern recognition, target detection, drone footage analyses, sentiment analysis, development of autonomous fighter jets, and testing of autonomous robots, swarms, and cyborgs—encompass all the domains of the USAF. Defense or offense, hacking or jamming, surveillance or reconnaissance, drone attacks or drone countermeasures—AI will likely touch nearly every area of USAF operations.

Traditional technologies of warfare are saturated in terms of precision, accuracy, consistency, speed, and efficiency. As opposed to conventional electronic warfare, "automated" or "cognitive" electronic warfare can help against enemy radars and jammers effectively and rapidly.

While AI is in an infancy phase now, we contend that the forthcoming decade will very rapidly witness the maturation of the AI designs, competencies, and capabilities from a sheer conception to ultimate domination. However, AI supremacy must be earned and not merely assumed. Currently, the nation's top adversaries, such as China and Russia, are pouring significant resources into military AI research and development (R&D). For the USAF (of 2030) to outpace its adversaries, it will have to be visionary, proactive, and it must invest at a higher or at least comparable level. In the AI Acceleration, today's research is going to be deployed as tomorrow's Air Force technology. Humans and machines and their subsequent interactions are at the heart of the AI acceleration. Figure 1 illustrates schematically the various levels of integration considered during the intellectual discussions that took place during the preparation of this report.

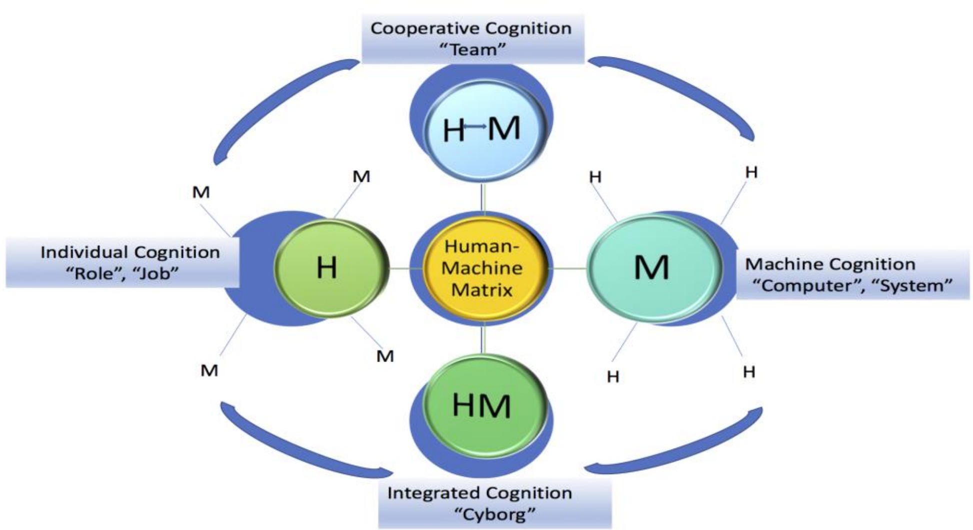

Figure 1: Schematic Representation of Various Levels of Human-Machine Interactions (*a conceptual organization of the report*)

In this figure, the logical divisions of this report are schematized. On the left-side (H; humans) represents the intellectual domain of the individual human service members. The context is augmented cognition (either enhanced or controlled by artificial intelligence) affecting individual human cognitive processing. The small M's (satellites to the H) represent the increasing use of smart machines by humans as they perform their jobs (e.g., sensors providing real-time data for decisions). On the right side (M; machines) represents technologies inclusive of robots, autonomous and conventional aircrafts, edge-computing and deep-learning systems. The small H's (satellites to the M) represent human service members obtaining resources from and for machine systems. Critical to AI acceleration, the diagram includes two components of hybrid human machine teaming. The top of the diagram (H-M; human-machines) represents the looser linkage of humans and machines operating more in the form of cooperative cognition teams. The bottom of the diagram (HM; human-machines) represents the tighter integration of humans with machines, where human-machine coupling creates an entirely new form of warfighter (e.g., something exemplified by the "cyborg" concept). The yellow circle at the center of the diagram represents the entirety of the human-machine matrix in the contexts of artificial intelligence and augmented cognition, the scope of the present report.

This report focuses on three key areas related to the AI Acceleration. The first area, machines, focuses on the opportunities to advance the capacity of machines, including robots, through the use and application of AI. The second area, humans-machines, explores new directions associated with the ways in which AI and augmented cognition enhance and support the integration of hybrid human-machine systems. The third area, humans, considers how systems that can directly interact with the human body and brain, including those that employ AI, will affect the training and performance of USAF personnel in 2030. For each of these areas, the ethical, legal and social context is of paramount importance. On the one hand, it is critical to invest in research to develop machines, systems, and technologies that are adaptable, flexible, robust, safe, and secure. On the other hand, it is essential to invest in the implementation of AI from the standpoint of personnel and training to create a force that is capable of effectively operating and maintaining the machines and systems. Crucially, this would include data and systems architects, that is leadership positions that orchestrate integration and exploitation of data across all scales. In 2030, humans will still be primary to overall USAF operations, from logistics to maintaining or controlling warfighting machines, systems, and technologies. With humans and machines interacting with each other, we see a continuum of interactions that are bracketed at one extreme by "integrated cognition," or more colloquially, "cyborgs" (i.e., tightly coupled man-machine systems that essentially act as a single mind). At the other extreme can be found "cooperative cognition" or human-machine teamwork wherein members of a human team are substituted with autonomous and self-directed machines (i.e., an autonomous wingman or navigator). Within these extremes are a range of intermediate possibilities. For example, "centaurs" are humans and machines that work tightly together on the same goal but that retain some independent identity.

Table 1 lists the status of USAF in the three areas (Machine, Human, and Human-Machine) as it stands today, and as it would be by 2025, and finally by 2030.

Areas	Today	2025	2030
Machine	Machine learning, Deep Neural Networks, Bayesian, Neuroevolution, GPUs, Cloud, Gb/s comms, reinforcement learning, cognitive robotics, CMOS, highly specific automation, limited robot applications, wearables, IoT, teleoperated vehicles. Semi-autonomous	Self-driving vehicles, neuromorphic applications, robots in some service vectors, smart health (real-time physical monitoring), edge processing, intelligent (sort of) assistants, hybrids of Bayesian, NN, Evo.	Quantum computers, advanced neuromorphic hardware, low power, rad hard, robot assistants, strong artificial intelligence, swarm intelligence
Human	Human teams, online learning, traditional classroom instruction, computer and simulation-based training	Personalized instruction-enriched with data input and learning trajectory modeling; implemented through virtual and augmented reality. Improvements on AI, data mining, and hardware technologies. Improvements in affective computing	Theoretical basis for optimizing human cognitive and physical performance through training, physical conditioning, epigenetic and genetic enhancement, diet, supplements, etc., mature and pervasive applications of VR & AR, contextually-aware biometric data collection for individuals, teams and organizations, microanalysis of knowledge and skills associated with jobs and abilities to select and train that extend from early K-12 to retirement, established markers for susceptibility to performance degradation and mental health effects of physical and mental stress with techniques for real-time management
Human-Machine	Tools, prosthetics, manuals, haptics, medical devices, serious gaming, AI assistants (e.g. Siri)	Co-adaptive information and software systems, neurotechnology implants, CRISPR-type manipulation to optimize brain-machine interfaces	Cyborgs, human-machine combat teams, cyber-domain sense enhancements for human operators

Table 1: The Status of the USAF today, by 2025, by 2030

a. Process

To study AI Acceleration and how this trend might impact the USAF of 2030, a broad interdisciplinary and extremely specialized expert team meticulously deliberated throughout the study period (from March 1, 2018 to June 30, 2018). The efforts and deliberations were finally made concrete in the current report, titled "*The AI Acceleration: Implications for the US Air Force of 2030."*

The study brought together over 100 leading academic, industry and government scientists. In terms of the process, the expert community convened online and, with a subset, face-to-face during the second quarter of 2018 in an "NSF Ideas Lab" format. These activities were facilitated by Knowinnovation (KI), a group that has extensive experience in facilitating innovative and interdisciplinary scientific advancement through both face-to-face and virtual interactions. Specific timeline details and components that helped to conceive the report are as under:

- **Virtual Think Tank & MicroLabs (Preparation):** To capture broad expertise, a virtual community was assembled that included over 130 active members (listed in the appendix). The virtual think tank members participated in online discussion forums and the exchange of relevant resources. Additionally, three MicroLabs (90-minute, highly interactive, online events) were held (April 30, May 1, May 2) to discuss biohacking, reverse engineering the human brain, and the future of robotics. Each MicroLab was designed in a highly interactive manner and included participation from approximately 25 virtual think tank members who contributed both in plenary discussions as well as breakout assignments. The MicroLabs served to engage the broader community, stimulate the thinking of the Ideas Lab participants, and provide a foundation for preliminary ideas for the report.

- **Ideas Lab (Action):** In the action phase, a face-to-face Ideas Lab was conducted at Vernon Smith Hall, George Mason University, from 05-07-18 to 05-11-18. A group of 25 experts participated (see their biographies in the appendix) in activities that identified signals of potential futures; explored the implications of these signals on the USAF of 2030 and the warfighting domains; and synthesized vignettes that captured and communicated the group's thinking. Simultaneously, additional online MicroLabs were conducted to seek the feedback of over 100 remaining Virtual Think Tank members who did not attend the Ideas Lab. The Ideas Lab led to a rough draft of the report.

- **Post-labs (Culmination):** Following the Ideas Lab, a subset of the virtual community actively worked on finalizing the report. This draft was shared with the entire Virtual Think Tank, and two additional online MicroLabs were convened (June 11 & 12), to solicit and incorporate the feedback of the broader online community.

b. Scope

This report expounds on the current and a predicted landscape of Artificial Intelligence and Augmented Cognition in the USAF of 2030. The scope of the report inclines/gravitates around the following stated objectives.

Primary Objective

The primary objective of the report is to illuminate the 2030 technology horizon for AI in the USAF context.

Secondary Objective

A secondary objective is to facilitate the building of a community of USAF aligned experts who can provide continuing advice to the USAF as an external advisory committee.

Final Objective

The ultimate objective is to facilitate the discussions necessary to invent the USAF future in AI while building a pipeline of technological expertise in AI to avoid or respond to strategic surprise in this area.

2. Machines

A. Background and Current Status

In the past decade, there has been rapid progress in AI and Autonomous Systems. While these changes are exciting and promising, we view these current systems as having limited domains that can be employed only for specific tasks. An extremely pessimistic, but realistic, view claims that no operational and realistic demonstrations of robots exist for commonplace jobs today because of their compositional task complexity (Brooks, 2017). This is even more pointed in the areas of interest for the Air Force, which are far more dynamic and extreme than a factory floor worker.

Therefore, we see a need to develop machines and algorithms that can operate autonomously over the long-term in the extreme cases of air and space, replacing and in some cases transforming current capacities. Changes will not occur along existing trend lines: cyberspace is a rapidly evolving, highly dynamic environment where non-linear changes will most likely disrupt expectations. It is critical to invest in research to develop systems that are adaptable, flexible, robust, safe and secure.

Aspects of machine transformation

Cognizant systems exhibit high-level awareness beyond primitive actions, in support of persistent and long-term autonomy.

Taskable systems can interpret high-level, possibly vague, instructions, translating them into concrete actions.

Reflective systems can learn from their own experiences and those of other entities.

Ethical systems should adhere to a system of societal and legal rules, taking those rules into account when making decisions.

Affective Systems know the importance of situational variables, feelings, and emotions.

Knowledge-rich systems employ a variety of representation and reasoning mechanisms, such as semantic, probabilistic

B. USAF in 2030

By 2030, anticipated and unforeseen changes will affect the Air Force's operations in air, space, and cyber. Machines will become increasingly smart, adaptive, and interconnected over the next decade. Computing architectures added to machines will become increasingly useful for supporting logistics, smart defense, and lethal offense. Informed in part by the National Science Foundation's Smart and Autonomous Systems (S&AS) program, we see the transformation of machines towards capability of autonomous operation in the face of uncertain, unanticipated, and dynamically changing situations. Five aspects of machine transformation that are most challenging and where we see the need for decisions and research are: 1) cognizant, 2) taskable, 3) reflective, 4) ethical, 5) affective, and 6) knowledge-rich.

To achieve this, we have identified several themes to be addressed:

I) Aircraft Technology - innovative propulsion, advanced stealth, autonomous aircraft, and coordinated swarms will make up a massive portion of future aircraft. Such systems will require more intelligence, autonomy, efficiency, and resilience.

II) Intelligence and Autonomy - long-term autonomy will require advances in intelligent systems that can operate in uncertain conditions.

III) Cyber Security - future cyber systems and robots must protect themselves from being compromised, and their mission may be to ensure other systems are not compromised.

IV) Alternative Computing Architectures - Given the slowdown in traditional integrated circuit improvements and the physical limitations of ever-smaller transistors, there is a need for novel computing methods capable of providing Moore's Law-like scaling.

V) Energy Efficiency and Resiliency - long-term operation will require readily available and reliable power sources, efficient computation, and efficient propulsion. Operating in extreme environments will require systems to repair themselves and possibly find the materials necessary for those repairs.

These themes are illustrated below.

I. AIRCRAFT TECHNOLOGY

Figure 2: F-35A Aircraft. The F-35 Lightning represents the latest human-piloted fighter aircraft operationally deployed by the USAF. This machine offers a suite of sensors and compute-power to facilitate air superiority for USAF combat pilots (photo credit: USAF.mil).

Aircraft Technology is of great interest to the Air Force now and in the future. Artificial Intelligence and autonomy will influence the design of future aircraft. Recent experience with UAVs shows that missions previously possible with manned aircraft can now use unmanned aircraft, thus, lessening the risk to human pilots. In the future, swarm intelligence, low power, long range vehicles, and hypersonic aircraft are all possible ways to further the emphasis on UAVs. The development of both defensive and offensive unmanned aircraft operating in primary (e.g., delivering payloads) or secondary (e.g., reconnaissance) should be a priority.

a. Hypersonic Vehicles.

Description: Hypersonic aircraft, weapons, and vehicles are likely poised to present a new arena of air-based warfare and new requirements for air superiority (Sherman, 2017). The term hypersonic generally refers to greatly exceeding the speed of sound, and by some definitions, hypersonic technology has a long history. For examples, in the late 1940s, the German V-2 achieved speeds exceeding Mach 5, and the USAF X-15 exceeded Mach 6 before the end of the 1960s. Improved technologies paired with evolving global policy and defense systems have renewed the tactical need for these systems.

State of the art: Currently, the USAF has tested the Advanced Hypersonic Weapon (AHW) for the Prompt Global Strike effort. In a 2011 test, the AHW traveled over 2,300 miles in under 30 minutes to successfully hit a test target. This new and developing set of capabilities offers strategic advantage and novel adversarial threats.

Several foreign nations also have active research into hypersonic systems. China has launched several well-publicized tests within the last several years. Given the high speed and advanced flight characteristics of these vehicles, defense is a difficult challenge.

Goal: Artificial intelligence and machine learning may improve the efficacy and feasibility of hypersonics in a variety of ways. Central among these are intelligent, robustly automated target recognition and adaptive, rapid mission planning. Size, weight and power constraints, sensing restrictions, and high computational requirements limit current techniques. However, improvements in learning algorithms and computer architectures may enable unprecedented capabilities in the future. Additionally, future machine learning algorithms may power advanced detection, identification and tracking systems. Given the unique capabilities of hypersonic vehicles, traditional defense methods may be ineffective. Lastly, self-guided autonomous systems will almost certainly be necessary for effective counter-hypersonic measures or future swarm-hypersonic systems.

b. Low Power Gliders.

Description: Like a bird of prey, glider aircraft will offer extended, sustained flight at low energy and fuel costs. While such aircraft do not necessarily have to be autonomous, their economy of operations and sustained length on a station, make them an amenable platform for deploying AI.

State of the art: Current implementations of low-power and long-distance aircraft exist, though their utilization is limited to experimental tests and some reconnaissance.

Goal: Leveraging thermals and air currents, solar powered gliders may be able to operate for extraordinarily long durations. These systems could be used for attack, defense, or reconnaissance missions where long-term loitering is a key differentiating tactical capability.

During swooping engagement, advances in materials and reconfigurable design may allow a glider will change its shape (e.g., lose or retract wings) to drop rapidly and accurately toward its target. Given the use of solar power, low-power onboard computation will be necessary for autonomous systems, evasion, on-board Automated Target Recognition (ATR), communications and control. Additional development in non-von Neumann computing systems, such as neuromorphic processors, may aid in this effort. Such a platform offers a low-cost agent in asymmetric warfare.

c. Swarm technology.

Description: In the last few years, we have seen the advent of cheap, and readily available small size robotic systems (Rubenstein et al., 2012) as well as small Unmanned Aircraft Systems (sUAS). The emerging field of swarm intelligence (Bonabeau, 1999) inspired by biological principles, employ simple and distributed nature of coordination where global behaviors emerge from local interactions, and they are not explicitly programmed (Brambilla, et al., 2013; Dorigo 2016; Valentini et al., 2017). Swarm behavior, as we know it now, is the collective motion of many self-propelled entities called boids. Swarms have the potential to be modular and reconfigurable both in shape and their control (Matthews et al., 2017). Swarm intelligence has advanced to the point of offering significant offensive and defensive capabilities for the Air Force.

State of the art: The current capabilities include: 1) a photophilic solar panel built into each boid that can power ultra-lightweight batteries for up to 90 hours of use; 2) node-to-node communications that enable swarming behavior that can retrieve boids from swarms that up to 300 feet into the zone of attraction; 3) self-repair of boids damaged at less than 30% integrity; 4) boid-to-boid substitution in case of loss of boids during deployment.

Goal: Future swarm technology could have a significant offensive and defensive impact for the Air Force. In addition to the basic rules of swarming (e.g., move in the same direction as neighbors, remain close to neighbors, avoid collision with neighbors) the capacity to engulf a target and freeze-and-squeeze in place, could neutralize a target, or destroy a target by delivering explosives on the scale of an IED. Using AI technology for assured distributed system intelligence, which will enable the swarm to adapt to battlefield obstacles, including being able to disperse and re-form around projectiles and non-target obstacles. Responding to instantaneous in-flight reprogramming by a centrally located, authenticated smart agent that may change the mission target, the extent of swarm lethality, or to be removed from the battlefield. The swarm may self-organize into a single mesostructure to allow for the swarm to gain solar access and to be camouflaged before mission-critical timing. In this way, the swarm could be transported as either a single mesostructure or as flat entities. Furthermore, the swarm could autonomously change colors or use mirrors to become difficult to detect. Future swarms will be able to operate in extreme environmental conditions, including outer space. Artificial Intelligence and machine learning will be crucial in advancing processes for cost-effective, rapid design and manufacturing. Current creation of mechanical and computer systems is labor intensive in both initial design and later testing. In particular, we are moving away from systems that are programmed by people to operate in a certain way to machines that are capable of learning and adapting, and in some cases, developing novel behaviors that the developers may have never envisioned. Increases in computing capability and algorithms (machine learning, evolutionary algorithms, fluid dynamics models) will enable accelerated design processes.

d. Countermeasures against Swarms.

Description: Swarms of UAS could be a significant threat. The swarm of drones' technology is very affordable and attainable from many sources worldwide. Besides, the tactics of using UAS swarms as weapons are evolving and changing based on specific targets and defense strategies.

Existing counter UAS approaches today cannot rapidly address this threat. A solution that couples detection/ID, tracking, and softkill neutralization in an autonomous swarm system provides a means to solve this problem in a reusable manner that can scale up to deal with multiple simultaneous autonomous threats. Such economically-viable solutions require a level of both local and long-range situational awareness that can be distributed among the swarm agents in an autonomous manner.

To counter swarm UAS aggression, defense strategies range one-to-many and many-to-many, and it requires new technology developments in three primary areas: Detection and ID, Tracking, and Neutralization. Detection and ID must deal with tactical UAS that fly low, slow, and are small. This is difficult over even restricted volumes of airspace on the scale of a small city (<4km). Tracking capability is required to enable reliable identification and countermeasures, whereas, neutralization is required for eliminating imminent threats.

State of the art: As for detection and ID, current SOA approaches such as radar can easily be confused by birds and ground clutter, and do not enable reliable classification and identification of a potential threat. As for the tracking capability is related, the existing capabilities are limited to traditional state-estimation approaches and are not accurate to predict non-linear behaviors or movements of an increasingly agile fixed wing as well as small commercial quadrotors, let alone non-cooperative or evasive autonomous systems. Finally, the current neutralization approaches have focused on hard kill methods that can cause collateral damage and often suffer from high "overkill" cost.

Goal: Recent research can address the limitations of SOA methods in all three of these critical areas while enabling rapid deployment at low cost. In general, multimodal sensors (vision, audio, radar) with machine learning and data fusion are pivotal. Larger area detection using multi-static radar coupled high resolution motion-based visual detection and ID algorithms using deep networks provide a rapid capability to distinguish between UAS and birds or clutter over city scale ranges. Novel flow-field control and tracking methods can enable the movement to and mirroring of one or more threats for enhanced identification and preparation for neutralization. In traditional warfare, capturing mid to high-level officers was often more valuable than killing them. Similarly, countermeasures that deploy capture methods such as net guns to grab an evasive threat and return it to a safe zone are preferable to hard kill solutions.

Future commercial wireless networks (“5G”), with their very broad bands of operation and steerable millimeter wave beams, may offer new capabilities to counter swarm threats. 5G networks, though very much still in the initial stages of specification, development, and implementation plan radio bands in the current bands (roughly 600 MHz to 6 GHz) but also bands around 26, 28, 38, and 60 GHz with steerable beams and huge Multiple Input Multiple Output antennas. These networks will be available in many of the likely target zones for swarm attacks, and, therefore, may offer a unique asset to recognize, track and disrupt swarms of small UAS.

II. INTELLIGENCE AND AUTONOMY

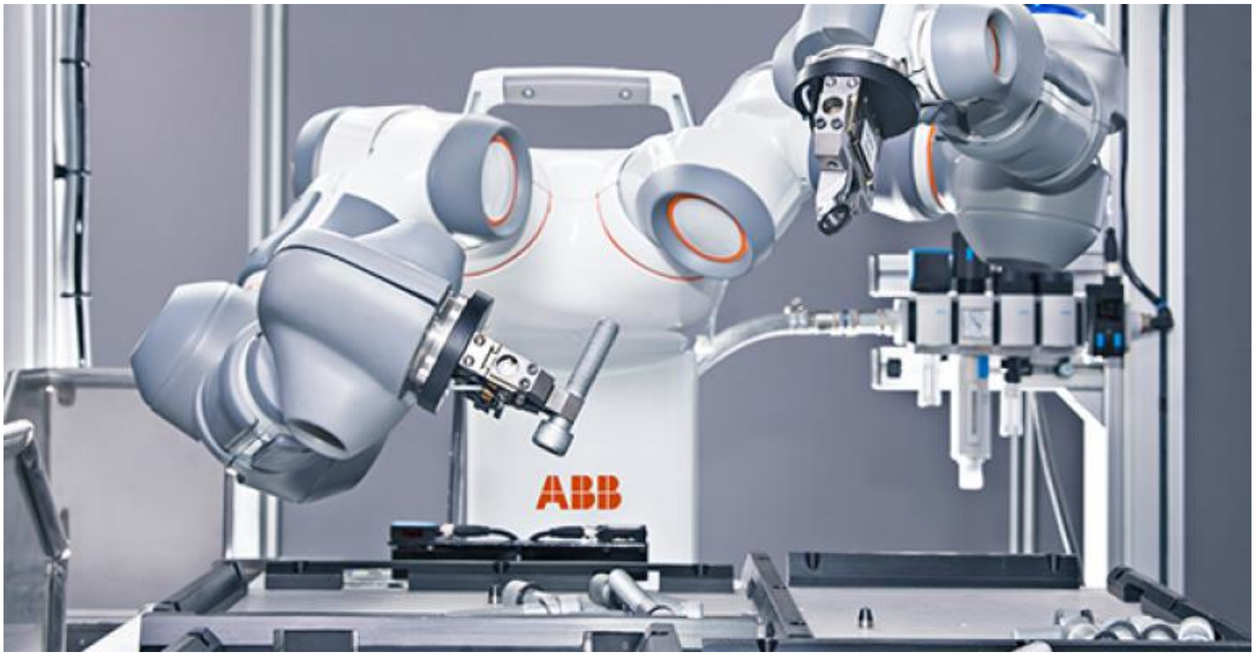

Figure 3: YuMi Robot. Short for “you and me,” the YuMi is a dual arm robot designed to achieve the flexible production needs of the consumer electronics industry (photo credit: ABB).

Intelligence and autonomy can be built into systems at varying levels of capability or capacity depending on the scope of the mission. Intelligent systems can sense the environment, learn from it, recode information, and deduce and determine an action based upon latest information. Autonomous systems can alleviate the load on human warfighters, allow the warfighters to operate at a higher level (thus dealing with big-picture strategic facets of warfare), act in extreme environments, and may be able to make decisions more rapidly than humans.

An intelligent machine is one that can accomplish its specific task in the presence of uncertainty and variability in its environment. The machine’s ability to monitor its environment, as well as allowing it to adjust its actions and functions based upon what it senses, is a prerequisite for intelligence. In the future, intelligent machines will add on types of intelligence, autonomy, and cognition that are different from and orthogonal to or beyond human capability, such as seeing invisible events by virtue of perturbed physical events of Wi-Fi radio signal (Zhao et al., CVPR, 2018).

Examples of intelligent machines include industrial robots equipped with sensors, computers equipped with speech recognition and voice synthesis, self-guided vehicles relying on internal vision or mapping rather than external signals, and objects capable of target identification and differentiation. Three major capabilities are generally built into intelligent autonomous machines: sensors, actuators, and controls. The class of computer programs known as expert systems can access databases explicitly built for tasks; their power and limitation are in the available data. Deep learning algorithms are implemented by interacting with a supervisor in a controlled learning environment, and then stop learning altogether when embedded into the environment for function. It is indeed a current major challenge to develop AIs that learn continuously and without forgetting prior learning (i.e., catastrophic forgetting problem).

While expert systems, deep learning, and convolutional neural networks may appear to be 'intelligent' in ways like humans, they are constrained by the extent of algorithmic capability built into them or data available to them. Therefore, they are devoid of the degree of rational choice or judgment or intuitive decision making that characterizes human expert decision making. Rational and intuitive judgment based upon complex input factors and variable outcomes are currently beyond the capability of intelligent, autonomous machines or deep learning systems. Moreover, current systems are not "explainable," that is, they cannot communicate the reasoning behind their choices (Sukkerd, 2018; Lomas 2012; Wachter, 2017). And yet, these systems have clear advantages: they process information (e.g. images) tirelessly, cheaply, in extraordinary quantity and a rate much faster than humans. Further research into the use and scope of intelligent, autonomous and deep learning machines is needed. The research will continue in parallel in these two broad areas, although we expect the two strands to converge at some point in the future.

Development of the next wave of AI algorithms will endow the emerging field of autonomous systems with the ability to perform lifelong learning like humans, as well as transferring knowledge and skills. These algorithms will be informed by studies of human brains in action using such techniques as cortical surface recording. Research in these areas is at an early stage (Kirkpatrick, 2017; Hassabis, 2017; Tyukin, 2017). Operating together, these systems will similarly be able to combine experiences to emulate the cultural learning essential to human endeavors. Such enhanced systems can continually improve their performance and update their knowledge unsupervised, rapidly adapting to unforeseen context, and learn and consolidate new tasks without forgetting old ones. In addition to deep neural networks, the use of other types of machine learning such as reinforcement learning, decision trees, and Bayesian learning will be pivotal.

a. *Bio-Inspired Autonomous Systems and Artificial Intelligence.*

Description: Autonomous systems can take inspiration from biology. Biological organisms have the enviable capacity to multi-task and readily adapt to new situations, with survival skills and self-repair further enabling adaptability in a vast array of conditions. Biological systems tightly couple brain (i.e., control systems), body (i.e., shape, sensors, actuator, and power systems), and environment (i.e., task domain). Too often roboticists focus on a particular aspect, and this can limit their operation. Overall, the field of autonomous systems needs to take a more holistic approach. Brains and bodies co-evolved to develop more successful behaviors in a dynamic, challenging world. However, the body often leads the brain, and its morphology is critical to what we call intelligence (Pfeifer & Bongard, 2006; Krichmar, 2012). The notion of ‘‘morphological computation’’ in which processes are performed by the body and its exploitation of the environment, rather than by a central control system (Pfeifer & Bongard, 2006), could significantly impact how we understand the brain, body, and environment (Clark, 1996), and how we design future autonomous systems.

State of the art: In general, this is an exciting time in AI and Artificial Neural Networks (ANN)/Spiking Neural Networks (SPN),[2] manifesting as the AI Acceleration. We see artificial systems show better-than-human performance in certain tasks (Mnih et al. 2015; Silver et al. 2016). However, there are limitations to this current, simplified approach. It works in a limited domain, often requires lengthy, specific training, and may not be able to address many of the behaviors that we take for granted, but attribute to intelligence (Hawkins, 2017; Larson, n.d.) To address these limitations, Jeff Hawkins (2017) recently argued in IEEE Spectrum that intelligent systems must incorporate critical features of the brain: 1) Learning by rewiring; i.e., we learn quickly, incrementally, and over a lifetime. 2) Sparse representations; i.e., biological systems are under extreme metabolic constraints and need to represent information efficiently. 3) Embodiment; i.e., sensorimotor integration is observed throughout an intelligent system. 4) Value systems; extracting saliency from the environment and responding appropriately (Friston, 1994; Krichmar, 2008), and 5) Prediction; using past experience to be more successful in the future (Clark, 2013). Predictive coding strategies, such as hierarchical Bayesian systems or recurrent neural networks can develop internal models that predict value, reduce surprise or entropy, and thus minimize energy utilization (Friston, 2010). Beyond these features, the energy requirements of the human brain (25 watts of power) provides an existence proof for artificial intelligence efficiency in the future.

Goal: Future autonomous systems need to address all five of the above brain’s features holistically to demonstrate behavior that can generalize across multiple task domains and over longer timeframes. A fruitful approach toward a genuinely cognitive system is to take inspiration from the brain and body of natural systems. Intelligent physical systems can change their environment and can create sensory information by their actions, thus increasing the system's information processing (Rosch et al., 1992).

b. Edge Processing.

Description: Trends in civilian, as well as military systems, point to directions where sensing, processing, and actuation is situated in distributed platforms. The emerging Internet-of-Things (IoT) are cyber technologies (Atzori et al.,2010), hardware and software, that interact with physical components in environments populated by humans. IoT devices are often thought of as the “edge” of a large sophisticated cloud processing infrastructure. Processing data at the “edge,” i.e., near the sensory-motor systems reduces system latency by removing the delays in the aggregation tiers of the information technology infrastructure (Hu et al., 2015; Shi et al., 2016; Mao et al.,

[2] Spiking Neural Networks (SPN’s) are generation beyond typical ANN’s and can handle time-dependent data. These are much more biologically plausible approaches (Long, 2016).

2016). In addition to minimizing latency, edge processing may increase system security and mitigate privacy concerns when processing data in the cloud.

State of the art: Companies such as Microsoft, Google and Amazon are devoting significant efforts to Edge Processing. For example, Microsoft's Azure Sphere is a managed Linux operating system, microcontroller and cloud service.

Goal: Autonomous operation and decision making coupled with real-time ability to do local processing before transmitting the data/information necessitates feature-driven "intelligent" sensing nodes with extreme energy efficiency.

III. CYBER SECURITY

Figure 4: Cartoon about Cyber Security (Photo credit: *The Economist*; May 07, 2009).

Cyber warfare, both offensive and defensive, and cybersecurity continue to increase in importance. This is particularly the case with machine learning systems where AI relies on mining large datasets. Trust in intelligent machines can only be maintained through security and verification, and the development of sound internal controls and practices that protect against external threats. A critical area of research is "explainable" systems wherein intelligent autonomous systems are able to communicate their choices and values to human operators or teammates (Sukkerd, 2018; Lomas 2012; Wachter, 2017). In 2030, most systems will communicate via secure encrypted channels and utilize distributed ledgers (e.g., blockchains) for independent transaction verification. Intelligent machine sentries will likely be autonomously observing behaviors and taking proactive measures to prevent attacks. Autonomous agents may need to be isolated from any electronic network communication for maximum security while executing predetermined missions.

a. *Defensive Cyber Systems.*

Description: Currently, the number of attacks against systems are blocked through automated routines. As autonomous agent technology matures, there will be more reliance on cyber warriors to defend networks and computer systems. The analog is white blood cells or leukocytes. In that regard, while blood cells are genetically programmed (through evolution) to defend the body from invaders. Cyber sentry agents, like white blood cells, can be predetermined to defend a network from bad actors adaptively.

State of the art: Static protection measures like firewalls and antivirus

Goal: In 2030, the static protection measures like firewalls will probably be inadequate. More likely is the fact that active defensive measures will be necessary to address a highly adaptive threat. Again, the biological analogy is strong. Like with viruses, the bad actors are continually evolving to avoid detection and to circumvent static defenses. Adaptive autonomous cyber sentry agents will be required to address this ever-changing threat. Currently, firewalls are in an arms race with evolving attack vectors attempting to learn about the defense adapting these attacks in near real-time, often with minimal if any human intervention and those on the defense side adapt their defenses to these evolving attacks. Such systems will need to improve and utilize more advanced AI technology to defend systems against these attacks.

Vignette: On January 17, 2023, the United States and other northern hemisphere countries experienced continent-wide signals outages due to rogue action by terrorists. Called the "1-17" attacks, the action took out multiple communications satellites in geostationary Earth orbit. Captain McIntosh was put in charge of the Air Force Task Force to investigate the attack and plan the response. Services were restored by piecing together alternative satellite connections at low Earth and middle Earth orbits, but the outage was a wake-up call to the many stakeholders in the United States. An action was needed to address the vulnerability of satellites at geostationary orbit. The assault that took out the satellites was found to be a relatively simple deployment of rocks and stones that stripped satellites of external materials. How the assault was launched, and the rock swarm set into orbit, was not disclosed by the Task Force. Captain McIntosh organized a planning effort by the United States Air Force, together with NASA, the intelligence community, and private sector companies, to plan investment into the action against space-based terrorism. A Task Force was formed to develop specifications for intelligent and robust satellite systems for ISR-type missions. The plan began by specifying the need to build new intelligent satellites that could be maintained and upgraded from space. The first goal was to harden future assets for Earth and outer space use. Secondly, the Task Force determined that replacement parts and interim small satellite capabilities would need to be manufactured in space at the International Space Station. Plans went into place to design smaller, more agile satellites that could be partly manufactured by 3D printers, and then could be repaired and maintained from space. These plans went into operation in 2026 and were ready for testing by late 2027.

b. Information aggregation, assimilation and scoring.

Description: Social media platforms and low-cost content creation create chaos of self-serving disinformation campaigns from a large variety of nations, businesses, political organizations, splinter groups, terrorist organizations and radical ideologues, dramatically distorting the perceptions and confidence of the American citizenry and warfighters. Political cohesion disintegrates as misunderstandings propagate and create additional avenues to create and exploit confusion. The ability of Air Force commanders to obtain political support and internal cohesion severely inhibit their ability to execute high-stakes operations and invest resources against future threats.

From intelligence to logistics to the application of force, AF operations are critically dependent on the veracity and security of the information they assimilate and exchange. For example, the use of lethal force depends critically upon the AF's ability to receive and believe the signals are indicating that such force is warranted and where it should be applied, and then to deliver and validate signals throughout the kill-chain securely. The capabilities implied in the boxed vignette might be used to mitigate information corruption, disruption, and confusion.

The distributed nature of processing, with data exchange across a multiplicity of physical and logical interfaces, introduces systems vulnerabilities that could be exploited by adversaries and hence the need for "assured" operation. Cybersecurity in these systems should not come as an afterthought but rather "ab-initio."

State of the art: Currently, the Air Force creates a large-scale machine learning system that is trained continuously on diverse sources of public data streams to provide analytics for each of these streams in real time. Some of the analytics are publicly available to engage and inform the public. The automation of these activities and their elevation within strategic and tactical operations will become increasingly important. Air Force commanders use the system to assess the current climate and inform political decision makers. Air Force personnel receive specialized training and additional sources of information to make valid judgments about the current state. Authoritative information sources ("experts") are used to supplement public data streams and inputs using secure, authenticated channels (e.g., "blockchain").

Goal: For added security, authoritative information sources ("experts") could be used to supplement public data streams and inputs using secure, authenticated channels (e.g., "blockchain"). In addition, the USAF will use intelligent cyber-physical systems that are currently investigated in a variety of sectors, including smart manufacturing (robots that work safely with people in shared spaces), smart grid and utilities (systems for efficient and effective transmission and distribution of electric power, etc.), smart buildings and infrastructure (active monitoring and control of buildings).

c. *Intelligent Satellite Deployment and Maintenance.*

Description: Given the growing challenge of contested space and increases in space-based-capabilities, it is imperative to establish intelligent and robust satellite systems for Intelligence, Surveillance, and Reconnaissance (ISR)-type missions. Since the satellites are expensive investments at special risk of cyber-attack, they are even more worthy of specific protections, which intelligent deployment and maintenance would provide.

State of the art: Conventional strategy placed the satellite as a sensor and a relay. Images and data are collected and transmitted essentially wholesale to ground-based data processing sensors. While this allowed for high-fidelity information in high-consequence decision making, increases in sensor fidelity have created an unprecedented bandwidth bottleneck. Limits in Size, Weight, and Power (SWaP) currently restrict available onboard computation. US DOD and IC assets in low earth orbit and geosynchronous orbit are increasingly at risk from kinetic attack. They are also potentially vulnerable to cyberattacks via compromise of uplink or novel close proximity manipulation by adversary maneuverable spacecraft. Such modalities must be anticipated well in advance and counter-tactics devised.

Goal: The Air Force should look to intelligent sensors capable of using context-aware saliency machine learning to allow reducing transmissions to mission-critical information. Systems must be robust and resilient by design. Additionally, machine intelligence can provide enhancements and annotations to remote sensing data enabling better-informed analysts and ultimately faster and more robust decision making. Algorithmic advancements will require concomitant improvements in computing performance-per-Watt, likely through the development of non-von Neumann computing architectures.

Advancements in material science, additive manufacturing, autonomous robotics, and AI may enable in-orbit repair. Additive manufacturing services may provide space-based modification and upgrading capability. Advanced variable-flexibility and solar-cell-woven materials may form the basis for modular, self-organizing maintenance robots. Ultra-low-power neuromorphic computer architectures may enable these autonomous or semi-autonomous agents with advanced decision-making and control system algorithms at stringent SWaP requirements.

IV. ALTERNATIVE COMPUTING ARCHITECTURES

Figure 5: IBM's quantum computing center at the Thomas J. Watson Center in Yorktown Heights, New York. The center holds quantum computers in huge cryogenic tanks (far right) that are airconditioned to a fraction of a degree above absolute zero (photo credit: IBM, Feb 2018).

The Air Force's future reliance on intelligent systems, long-range autonomous operation, and cybersecurity will require major advances in computing power. Given the slowdown in the traditional CMOS chip improvements and the physical limitations of ever-smaller transistors, it is commonly believed that we are currently facing an end or curtailing of Moore's Law and Dennard Scaling. This has motivated a renewed and enlarged interest in novel computing methods capable of providing Moore's Law-like scaling, such as neuromorphic hardware and quantum computing. A variety of fields and techniques are proposing a number of solutions, though many focus on removing the so-called von Neumann bottleneck—That data must be transferred between processor and memory. Processor-in-memory strategies are often at the heart of advantages promised by non-von Neumann systems.

The development of non-von Neumann computing platforms, and specifically, neuromorphic architectures enables next-generation processing (Aimone, et al., 2017; Conrad et al., 2017; Indiveri et al., 2011). By incorporating a processor-in-memory and event-based design, neuromorphic processors can provide three orders-of-magnitude strategic advantage in performance-per-Watt while being robust to radiation effects. Stochastic computation and fault tolerant algorithms yield radiation hard, robust performance. These specifications represent a synergy between big-data derived, biologically inspired algorithms and neural-inspired hardware.

Future computer architectures will allow for an increase in remote computation at low power consumption. This will allow for real-time, intelligent, and adaptive algorithms to be developed to preprocess, annotate and summarize collected information. These machine learning and AI algorithms may power region-of-interest detection, reserving precious bandwidth for mission-critical information. Additionally, the algorithms can annotate and infer objects, behaviors, and intent within the scenes and transmit these annotations as well. The result is that the receiving warfighter, analyst, or astronaut gains enhanced, real-time situational awareness at a lower cost.

a. Bioinspired Computing.

Description: Matching the information processing capabilities of biological neural structures in state-of-the-art silicon technology is still an open issue despite the stunning advances in microelectronics. The goals of endowing modern computer systems with industrial-strength robust bio-inspired sensors or tackling the challenge of silicon cognition have yet to be realized. Our lack of knowledge about the inner workings of brain function and behavior has contributed to this chasm (Tognoli & Kelso, 2014), and there is a need for further investigation in this area over the next decade.

DNA-Inspired Computing:

By 2030, DNA nanotechnology techniques will likely have matured to the point of providing the basis of object construction at nanoscale resolutions (Mathur and Medintz, 2017). This technology will facilitate the construction and deployment of previously unthinkable sensors and edge analytics.

Over the last half-century computer scientists, architects and engineers have envisioned building computers that match the parallel processing capabilities of biological brains. Over sixty years ago, the fathers of computer science Alan Turing (Turing, 1952) and John von-Neumann (Neumann, 1958) looked to the brain for inspiration in order to advance the science of computing. Roughly, twenty-five years ago, the connectionist movement emerged as an alternative approach to artificial intelligence for solving the hard problems in perception and cognition. Similarly, the deep neural networks revolution of today rely on the central doctrine in the connectionist movement that the cognitive abilities of the brain are a result of a highly interconnected network of simple processing units. These simple non-linear computational units abstract the function of neurons while synapses abstract the connections between neurons. The strength of the synaptic connections in networks of such units is determined through a learning algorithm.

State of the art: Research towards the engineering of custom large-scale digital bio-inspired integrated circuits has also begun with encouraging results. SpiNNaker is a System on a Chip (SoC), a massively- parallel digital neuromorphic computing architecture (Furber et al.,2013) based on an 18-core symmetric chip-multiprocessor where each core is an ARM968. A

SpiNNaker computer will consist of a million microprocessor cores interconnected via a switching network fabric. APIs and software have already been developed for the SpiNNaker system (Davies et al.,2010), hence an excellent platform to explore bio-inspired algorithms and architectures for cognitive computing. Other digital bio-inspired system architecture for energy-aware cognitive computing were developed by IBM under the SyNAPSE project (Modha et al., 2011; Merolla et al., 2011), and by HRL laboratories (Srinivasa et al., 2012).

Complementary to advances in large-scale hardware architectures have been the advances in large-scale software simulation and modeling environments such as Brian (Goodman & Brette, 2008), Nengo (Trevor et al., 2014). The close coupling of these software environments to the SpiNNaker architecture (Furber et al., 2013), Neurogrid (Varkey et al., 2014), FACETS wafer-scale system (Bruederle et al., 2011), and SyNAPSE project (Modha et al., 2011) is likely to facilitate the widespread acceptance of custom architectures for large-scale simulations as an alternative to high performance computing.

Goals: Neuromorphic engineering and other non-von Neumann architectures can provide low power processing (on the order of milliwatts or watts, compared to kilowatts for a GPU) and sensing for autonomous systems. For example, IBM's TrueNorth neuromorphic chip has deployed convolutional neural networks on autonomous robots and other embedded applications with minimal power consumption (Andreopoulos et al. 2016; Hwu et al. 2017). New chips are being developed, such as Intel's Loihi that will support embedded neuromorphic applications (Davies et al. 2018). In addition to running neural networks on specialized hardware, very low power neuromorphic vision and auditory sensors are being developed (Liu & Delbruck, 2010; Stewart et al. 2016). Similar to biology, these sensors and processors only respond to change or salient events, and when they do respond, it is with a train of precisely timed spikes, like a neurobiological system. The event-driven nature leads to power efficiency that's ideal for autonomous systems and robots.

b. Quantum Computing.

Description: The capabilities enabled by quantum computing stem from the novel and exotic physics that occur at the quantum scale. Fundamentally, a quantum computer can solve problems of exponential complexity using linear resources via parallel execution of probabilistic outcomes. A critical application of quantum computing is encryption and cryptography (Bennett et al., 2014; Biamonte et al., 2017). The much-heralded Schur algorithm proves that a sufficiently large quantum computer would effectively defeat modern cryptography methods (public-key, RSA). Additionally, due to the fragility of quantum states, quantum methods may provide extremely robust security (quantum cryptography). Despite these promises, severe limitations currently exist. One challenge is translating a computation problem into the structure required by the quantum computer. The most commercially successful quantum computer (D-Wave) operates using Adiabatic Quantum Optimization, further limiting its utility. Another key challenge is the limited scale of the current systems and the difficulty in increasing this scale. Current systems are several orders-of-magnitude too small for even simple applications of the Schur algorithm, for example. Although, growing interest in quantum computing has led to the existence of research-scale systems, some of which are publicly accessible

State of the art: Quantum computer (D-Wave) operates using Adiabatic Quantum Optimization

Goal: By 2030, the ability to ensure coherence of many quantum bits (Q-bits) in computers should be a solved problem. While it is still unclear what the physical embodiment of such Q-bits will be (atoms, electrons, photons or other exotic particles), the ability to maintain long-term coherence in the machine environment will constitute the critical step towards practicality. As a result, quantum computing will be embedded all military-grade encryption for the USAF. The same technology will allow routine decryption of all non-quantum encryption algorithms rendering them effectively useless for critical defense needs. Quantum encryption will secure all communication links between all USAF assets in each of its warfighting domains. In addition to quantum computing, there is also a possibility of analog computing to facilitate exa-scale computing at reasonable power consumption levels due to the massive parallelization described above.

V. ENERGY EFFICIENCY AND RESILIENCY

Figure 6: Mobile Solar Plus Energy Storage for the US Air Force (photo credit: CleanTechnica, Sept. 2016).

For machines to operate over extended periods of time or in extreme environments, they will require energy usage orders of magnitudes more efficient than exists today. In many operational environments, energy sources will be scarce. The machine's design and function may be dependent upon the type of energy source, as well as its availability and accessibility. Any plans for defensive or offensive machines must begin with the question of how they are powered, where fuel is located, how energy is stored and made available to the machine, and how long the machine can operate on specific energy units. Given the conditions where these machines will operate, machines and materials will need to operate in extreme environments that include outer space and cyber.

Resilience, as it is used in systems studies, is the capacity of a system to respond to a perturbation or disturbance by resisting damage and recovering quickly. Disturbances or damage of sufficient magnitude or duration can profoundly affect a system and may force it to reach a threshold beyond which a different regime of processes and structures predominates. Building systems of systems with excess capacity is often done to ensure battlefield resilience. Moreover, keeping these energy systems operational, they will need to be protected against cyberattacks that can disrupt energy system (Wei et al., 2010; Zhang et al., 2017).

The extended operation in potentially remote environments makes energy efficiency and availability of critical importance to the future Air Force for their aircraft, autonomous systems, and cybersecurity. Current battery technology improves only incrementally and slowly. While the boom of electric vehicles should create quick progress in energy storage technology in the years to come, presently it is the constraining factor for nearly every computing device or autonomous system. Very few new or transformative advances are anticipated right now for battery technology. Whether charged by fossil fuels, solar, hydro, or kinetic energy, battery life, and size are the limiting factor for battlefield computer-driven equipment.

a. *Battery Technology.*

Description: Batteries are bulky and heavy. In general, the fuel economy of a system is the relationship between the distance traveled or life needed, and the amount of fuel consumed by the machine. Initiating design with low energy specifications of low fuel economy is one way to ensure that the least amount of energy will be needed. This can mean requesting that any machine be designed as a low-energy system, one that autonomously powers down in normal situations when not in use. In hostile environments, the low-energy machine should keep a small vigilance observing smart hibernation. This can also help with noise levels on the battlefield.

Battery Energy Storage Systems (BESS) are an integral part and one of the most promising ideas to achieve better machine design. BESS can provide a variety of applications for solving issues presented by the intermittency of wind and solar. Moreover, it can smooth the load curve, substitute for transmission, and offer resilience against failures anywhere in the system design. The upward trends of BESSs have made battery technology a key factor in the design of autonomous vehicles and electric vehicles. Many research facilities and manufacturers are working on developing the better battery for such applications. The Energy Storage Association (ESA) has set a very ambitious target for “the deployment of more than 35 GW of new, cost-effective advanced energy storage systems” by 2025.

Great care and attention to energy storage systems are necessary to overcome the discontinuity in the renewable production in battery technology. A wide variety of options and complex characteristic matrices make it challenging to discuss in a linear fashion or to understand the available technologies. An overview of mechanical, electrochemical and hydrogen technologies, explaining operation principles, performing technical and economic features, are beyond the scope of this report but should be part of continuous scanning and monitoring on the part of the Air Force.

State of the art: Lithium-ion type of battery is considered to be one of the most promising technologies. Calling it a "dominant design," David and Alferd (2016) discuss at length how Lithium-ion batteries ascended in prominence in the near past. However, they also note limits to this trajectory, proposing other technologies to serve wide-ranging applications. In their latest work, David, William, and Nathaniel (2018) call flow batteries as one of the most prominent alternatives to Li-ion. They also forewarn that, because of Li-ion technology "lock-in," additional technological breakthroughs in battery technology might stall.

Goal: The USAF, if they were to take energy storage a challenge, they might concentrate innovative effort on the dominant design (Li-ion) and use it as a path to come up with other disruptive technologies such as solid-state batteries. Solid state batteries are getting attention for their superior performance[3] and lesser risk of fire (Reisch, 2017).

We assume that developments in battery technology will occur in parallel with these AI and machine learning technologies.

b. Self-Repairing and Self-Regenerating Systems.

Description: Physical and informational systems are developing self-repair and self-regenerating capacities. In this regard, 3D printing is a big new development. In extreme environments, one could conceive of intelligent machines with 3D printing capabilities that self-diagnose and self-repair (Sells et al., 2010). One other promising area of development is in the nanoscience where research is exploring self-repairing and self-regenerating materials for use in extreme environments. These materials could significantly enhance the resilience of Air Force systems in extreme environments like irradiated zones or outer space.

Self-healing materials are synthetically-created substances that can mend themselves without any need of outside diagnosis or human involvement. Generally, fatigue, environmental conditions, and damage caused during operation degrade materials by bringing cracks and other microscopic damages. With this degradation, the materials change thermal, electrical, and acoustical properties. Typically, manual intervention is required for periodic inspections and repairs as small cracks are hard to detect. As opposed to this, self-healing materials combat degradation through its unique repair mechanism that responds to the micro-damage (Gosh, 2008). Some self-healing materials are called as smart structures as they are flexible to adapt to different environmental settings according to their sensing properties (Trask & Bond, 2006).

State of the art: There is evidence in the research literature of biomimetic designs that they are successfully being used in the development of polymer composites.

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[3] A recent article (in French), says that the energy density advance from 150 Wh/kg for lithium-ion to 800-1000 Wh/kg in solid state. (https://www.latribune.fr/entreprises-finance/industrie/automobile/bientot-la-revolution-des-batteries-solides-780986.html)

Goal: Biomimetic designs require further research for them to be made useful to intelligent, autonomous machines.

C. Research Questions

The following research questions emerged as the team went on discussing machines and how the USAF could employ the machines by 2030. These questions are so rich that they could serve as separate areas for further consideration. For convenience and simplicity, we are combining the questions in categories;

Data-related:

- What kind of software-hardware architectural frameworks should be developed to process the vast amount of real-time data?
- How can machine learning enable intelligent data preprocessing and summarization to convey mission-critical information with high confidence?
- How can increased spaced-based ISR resources discourage the creation of false, malicious and destructively self-serving content?

Security-related:

- What security protocols are needed to protect the alternative high-risk investment in potentially disruptive technologies?
- How can we monitor systems to avoid surreptitious infiltration?
- What kind of new principal methods for verification, validation, and testing are needed?
- What are the protocols needed to determine poison-pill implementation decisions (e.g., a system has been hacked, how does the system determine when it must self-destruct)?

AI-related strategic issues:

- How do warfighters know when dealing with AI or human on own side and on adversarial side?
- In what way can machine learning help create machine learning systems in service of Air Force operations? For example, Google is currently using machine learning “for” deep learning to identify hyperparameters better. What could be the Air Force equivalent of these?
- What advances in materials and devices are necessary for artificial intelligence at microwatt power scale?
- What AI / ML resources would be required to create an intelligent sensing and exact remote computation?
- How would advance remote sensing capabilities influence political, social and psychological dynamics?

- How do we achieve a high probability of detection for low, slow, small threats reliably over city scale (4km) ranges with low false positives?
- How can the widespread implementation of dense millimeter wave communications networks (5G) be employed to manage, track or defeat swarms?
- How do we determine an identity of the class of UAS and its capabilities from behavior?
- Can detection and ID capabilities be developed that are low cost and rapidly deployable?
- What methods can be developed to accurately predict the movement of one or more threat UAS over both short (seconds) and longer (minutes) time scales?
- Can responsive Counter UAS capabilities outperform threat UAS systems adequately to enable mirroring and capture of threats?
- What methods can enable multiple UAS to be coordinated to counter one or more threat UAS?

Resiliency-related:

- What is the resilient computing architecture and hardware that can survive in extreme condition?

Autonomy-related:

- What research is needed to address whether AI will ever be autonomous in the kill-chain decision process?

Kill chain-related:

- What are the ethics associated with putting AI in the kill chain?
- What are the operational considerations of putting AI in the kill chain?
- How do we verify/validate the security of the kill chain?

3. Humans-Machines

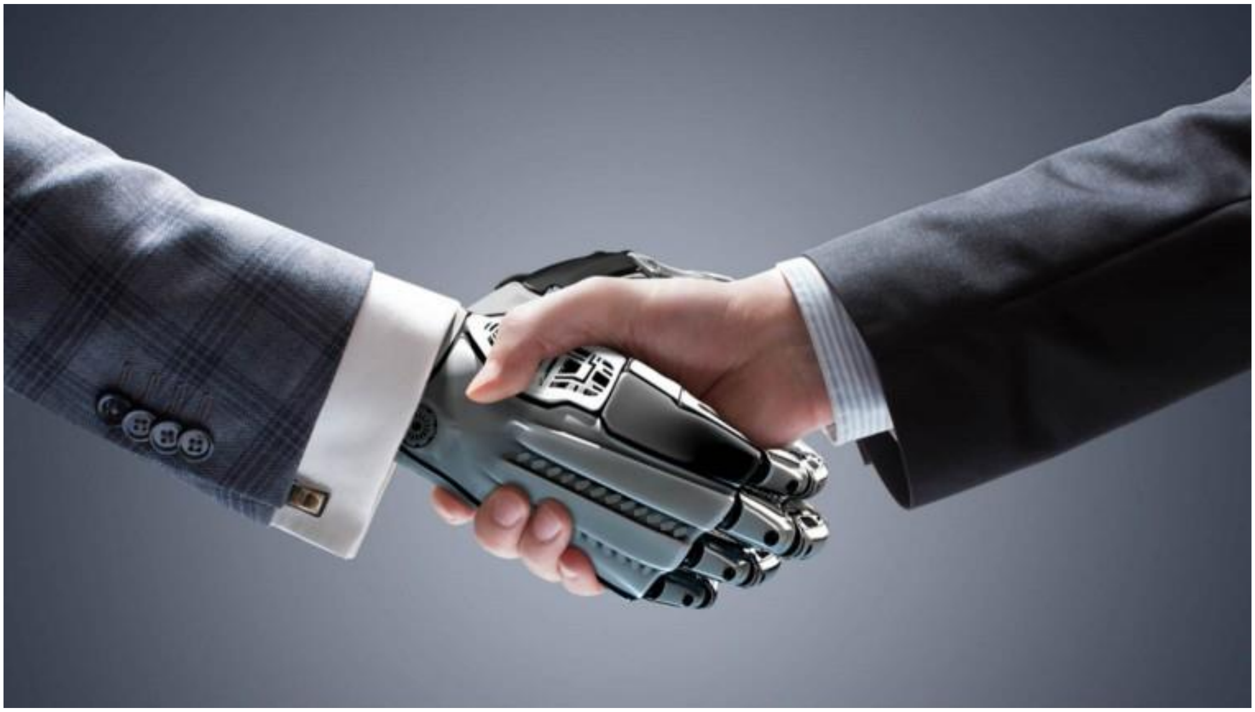

Figure 7: Man shaking hands with Robot (photo credit: Robotics Business Review).

A. Background and Current Status

In this section, we consider the AI Acceleration from the standpoint of human-machine interactions, broadly construed, including technological enhancement of human performance and human-machine interactions. Humans already interact with smart machines on a massive basis. In perhaps the most salient example, it is estimated that 2.5 billion humans currently use a smart phone (Statista), that is, they daily manipulate computing devices that greatly outperform the supercomputers of the 1970s.

For this report, “human-machine” refers to close coupling between humans and machines *in the operational context.* This report introduces a taxonomy of potential organizational structures for human-machine integration (see Figure 1, Section 1: Introduction). At opposite ends of the spectrum are *machine (M)* and *human (H) seen as individual operational units*; this is the standard for most of today’s operational paradigms where the human and machine have separate, *a priori* well-defined roles. Humans do employ machines to achieve goals that they alone define. But besides operational failures and functional limitations from the machine, or insufficient training to operate the machine from the side of the human, there is no frequent conflict of intention or regulation of action that pervades the realm of human-machine cooperation. This is in contrast with human-human teaming where task allocation, shared definition of goals and processes, and task monitoring generate intense and continuous interactions between the participants (Fiore & Wiltshire, 2016).

B. USAF in 2030

In the USAF of 2030, we envision a richer collaboration process where machines demonstrate intent, intelligence and autonomy or are able to seamlessly integrate with human and therefore, human and machine function become deeply intertwined (Figure 1, section 1: Introduction, vertical axis). In terms of the nature of the integration, at one extreme would be research breakthroughs that combine human and machine elements into a single integrated intelligence (see HM in Figure 1, section 1: Introduction), with technology that is directly connected to human senses and biology. At the other extreme, one might imagine human-machine teams where components of the team are most naturally seen as separate minds with their own ability to generate goals and make decisions in service of a joint task (H-M in Figure 1, section 1: Introduction). Orthogonal to the nature of integration would be the organizational structure being integrated, with its functional, social and ethical implications. For example, although cyborgs are most commonly seen as the fusion of one human mind with technology, technology might eventually allow the fusing of an entire air wing unit into a single “hive mind”.

In the 2030 horizon, and with careful leadership into an AI-accelerated mutation of its organizational structure, USAF has the potential to realize the transformational enhancements of human-machine teaming that will result in large gains in situational awareness, decision speed, operational and organizational agility. This will include the early adoption of advanced human-machine and brain-computer interfaces; the pervasive integration of wearable, micro- and nano-electronic sensors for physio-, psycho- and neuro-monitoring, feedback and closed-loop real-time interventions that will be connected with specific machines or broader command systems, especially valuable in extreme environments; an integration of teamwork between human and informational or robotic machines; the creation of virtual worlds mapping cyber-spaces and allowing human deployment in a spatially and informationally intuitive manner; and the mundane interactions with expert digital assistants, cloud-connected information systems with natural language processing capabilities that greatly shorten the distance between human and the information they operationally need. There was consensus about several broad themes to human-machine teaming.

I) Human Machine fusion to enhance individual performance: this area suggests emerging technologies to enhance human performance, including cognition, behavior and health.

II) Human-Machine teaming: this area points to emerging paradigms for the collaborative work in hybrid teams of human and machine

III) System-wide monitoring of collaborative Human-Machine performance: this area stresses the importance of a careful, continuous and dynamic oversight of those novel technologies.

These themes are elaborated below.

I. HUMAN MACHINE FUSION TO ENHANCE INDIVIDUAL PERFORMANCE

The combination of human and machines into an integrated system could take many forms and has the potential to (1) replace deficient aspects of human behavior due to inexperience, fatigue or pathology, or (2) add new repertoires of human behavior outside the realm of human psychophysiology (augmentation). The two are connected: often, technology breakthroughs, especially when invasive, are initially designed to correct for a disease that imposes a heavy burden on its sufferer (and therefore worth the risk), and then redeveloped to broader adoption when safety is established. Nevertheless, the key point is not whether the technology is implanted within an individual or not, but whether the machine and human work together as though they were a single mind and would be seen, essentially, as a unit of analysis within the organization. Many technological artifacts, even when not fully embedded in the body, become extensions of their owners' selves (Belk, 2013), suggesting a large capacity by humans to integrate technologies as integral part of their being.

Examples of technologies developed below include a warfighter with micro- or nano-electronic implants that allow a person to see a wider range of the electromagnetic spectrum (Chu, 2016), or to monitor and instantaneously remedy physiological challenges in extreme environments (Urban, 2008; Alam, 2015). It could also include a pilot controlling a plane as though it were an extension of his/her body through a brain-computer interface (Kryger, 2017), regardless of whether the pilot was co-located with the aircraft. It could be conversational technologies to discover information in the extended memory systems of a cloud, something at which machines excel (Jackson, 2007; Witte, 2008; Bakalov, 2013; Peinl, 2016).

Those fusion technologies will have, by design, an instantaneous operational advantage. But they might also contribute to retention and optimization of the USAF workforce. The basic human functions of perceiving, thinking and acting are supported by a brain and a body that age rapidly (Baltes, 1997; Schneider, 2000). They are also vulnerable to disease and have been limited by evolution to a subset of all the faculties available in the animal and technological world. The current USAF workforce has a sparse usage of integrated technologies for "cyborg" cognition and augmentation, and loss of functional performance from aging or disease is treated as ground for reclassification or dismissal, at lost for the training investment and the accumulated experience. Most of the augmenting technologies come with separate devices that the servicemen and women have to carry and install under demand (e.g. binocular, infrared camera, microphones, pharmaceuticals, nutraceuticals), that is, they cause carry load and have delayed and contingent availability.

In 2030, the USAF workforce will benefit from emerging research to integrate safe and robust cognitive, sensory, motor and physiological technologies as extensions of their selves to serve better and longer. There was agreement that research on human-machine integration should consider a broad perspective on techniques to integrate machines with the full range of human bodily systems including the peripheral and central nervous system (Serruya, 2002; Guenther, 2009; Nair, 2013), the musculoskeletal system (Walsh, 2006; Mengüç, 2006; Giancardo, 2016), the endocrine system (Appelboom, 2014, Zia, 2015), the viscera, the vascular system (Appelboom, 2014), immunological processes and even patterns of gene expression (Urban, 2008; Alam, 2015). Those enhancements will increase the operational performance of all servicemember recipients of those technologies.

a. Human-Machine and Brain Computer interfaces.

Description: Brain-Machine Interfaces or Human Machine Interfaces, collectively called BMI, are an active area of research whose maturation has a long history of military support. They are born from the goal of synergizing humans and machine so that human intent is seamlessly communicated to devices where they accomplish predefined operations with a gain in efficiency, speed and precision. The field divides in two approaches: 1) In invasive interfaces, electrodes are implanted in the body or in the brain, and the readout of their local activity allows a highly trained system (training often concerning both the machine algorithm and the human user) to perform some action in the world. Invasive interfaces are normally only applied to patients with severe deficits (locked-in syndromes, paralysis) due to the infectious risk and limited long-term stability (Wolpaw, 2006). 2) In non-invasive interfaces, sensors are attached or near the body or scalp (e.g. non-invasive electroencephalogram (EEG), functional Near Infrared Spectroscopy (fNIRS), wearable sensors) or dispersed in his/her operational environment (camera, microphones) to monitor state variables continuously and effect similar changes in the machines or computers with which (s)he interacts. Those technologies are a fast-moving research field with potentially immense tactical benefits for the USAF.

State of the art: BMIs now have a long history in the laboratory and in growingly broad applications, used amongst other for communication of verbal and written information and affective states (Chen, 2015; Brumberg, 2018; Murugappan, 2010), for control of computer applications, phones, device including virtual aircraft and drones and the Internet of Things (LaFleur, 2013; Jagadish, 2017; Chu, 2017; Kryger, 2017), for movement in rehabilitation and teleoperation (Wolpaw, 2004; Lebedev and Wolpaw, 2006; I Badia, 2013; Khan, 2014, Schettini, 2015; Farina, 2018; Zhao, 2017; Qiu, 2018), and to monitor and correct alertness and attention especially in the context of vehicle operation (Berka, 2004; Lin, 2010; Cao, 2014; Wei, 2018). The supporting technological developments, to make electrodes simpler to use (Spüler, 2017), to make the system more robust to contextual variations and portable, are also at a maturity point (Sagha, 2015; Tadipatri, 2017; Emami, 2018).

Goal: By 2030, USAF will deploy an increasing number of BMI technologies in the field to monitor alertness and other mental states related to decision, attention, memory, to control devices and computers, to communicate emotion and information, to teleoperate robots and machines. USAF would also benefit from investments in the research and development of rehabilitative technologies, both for the benefits of injured servicemen and women, and also with an eye on future technological readiness of implanted interfaces, as clinical research will be a strong driver for implanted technologies.

b. Neurostimulation Technologies to Augment Human Behavior.

Description: Neurotechnologies can read information from the brain and body and transmit information to the brain to modify its plasticity and function. This powerful paradigm has its roots in the extensive work on humans by Penfield and Jasper (1954), utilizing invasive microstimulation of the cortex of epileptic patients to understand the function of its many parts, a paradigm that sustained a (now abandoned) theory of the brain's functional localizations (one brain area per function, a view which has now conceded to a network theory of the brain). Two domains of application are training and augmentation of task performance. The former will be developed in section 5.II.e ("Neurotechnologies to Enhance Learning"). The latter is introduced here, in which devices are able to directly manipulate activity in the nervous system, without passing through the usual channels of sensory inputs. In the laboratory, this is accomplished with an array of methods: viral and non-viral vectors (Korte, 1996; Naldini, 1996; Bharali, 2005), gene editing (Heidenreich, 2016), optical and optogenetics (Han, 2009; Cardin, 2010; Bolus, 2018), focused ultrasound (Gavrilov, 1996; Deffieux, 2013; Lee, 2016), electrical and magnetic stimulation (McKinley, 2012; Vosskhul et al., 2018; Luu, 2016; Rao, 2014; Reinhart, 2017; Wilsch, 2017) and their combination. Two especially interesting examples of this technology are brain-to-brain communication and more generally brain-to-brain interface (Warwick, 2004; Hildt, 2015). This technology networks two brains for communication and control, whereby one organism (human or animal) whose brain is recorded can take control of another organism (control of movement) whose brain is simulated (O'Doherty, 2011) or along the same principles, two people can communicate rudimentary information (Hasson, 2012; Grau, 2014).

As mentioned before, there are a range of invasive methods. For example, (optogenetics, vectors) are overwhelmingly used in animal models, with human applications just at a tipping point at the time of this writing (Reardon, 2016).

Several non-invasive methods have been extensively studied in humans (magnetic and electric stimulation, and recently, focused ultrasound).

The shared goal of all those techniques is to access the nervous system to perform a functionally specific alteration of its dynamics, via modification of gene expression, excitability, connectivity and plasticity. Since there is a delay of several hundred milliseconds between receipt of sensory information and the simple-most form of behavioral reaction, this direct neural scheme presents tactical benefits for the rapid intervention of an intelligent algorithm rescuing or augmenting human behavior.

State of the art: The current USAF servicemen and women are only connected to command and control via telecommunication devices, but their brains have not been wired to intelligent support systems, lest for a few prototypes (Nelson, 2015). However, a conception of a warfighter equipped with EEG sensors and stimulators, for instance, has long been envisioned in the field.

Goal: The technologies are in early stage, but potential applications for USAF at the 2030 horizon and beyond are limitless (Nitsche, 2002; McKinley, 2012; Raco, 2014; Reinhart, 2017; Wilsch, 2017): automatic capture of attention, fast elicitation of motor reactions (technology-driven reflexes), enhancement of motor learning, augmentation/superimposition of perceptual information (Kupers, 2006, Raco et al., 2014), enhance spatial navigation (Losey, 2016), consolidate and reactivate memories (Liao, 2013), decision making, emotion, speech comprehension (Nitsche, 2002) and error monitoring to cite a few. There are also applications for pain management (Luu, 2016; Rasekhi, 2018), Parkinson's disease (Deep-Brain Stimulation for Parkinson's Disease Study Group, 2001), depression (Mayberg, 2005), stress and Post-Traumatic Stress Disorder (Novakovic, 2011; Widge, 2014; Bina, 2018) and many other clinical conditions (Ramirez-Zamora, 2018 for review) that are relevant to injured personnel.

c. Other Sensing technologies for Biofeedback and Closed-Loop Systems.

Description: Beside the neuro-sensing introduced in section (a) “Human-Machine and Brain Computer interfaces”, there is currently an explosion in sensor technologies offering further opportunity to monitor all systems from human physiology and its embedding environment (Hunter, 2010; Xu, 2012; Zhao, 2013; Appelboom, 2014; Banos, 2017). At all levels from the nanoscale (Moghimi, 2005; Urban, 2008; Xu, 2012; Alam, 2015) to the organ-level and beyond, in both invasive (Urban, 2008; Alam, 2015), wearable (Appelboom, 2014), interaction-based (e.g. analytics from user/smartphone interaction, Giancardo, 2016) and environmental schemes (the “smart home” concept, Harper, 2006; Hunter, 2010), there are now chemically or electronically engineered solutions to monitor health and interact with physiology and behavior in near-real time. The report group strongly felt that a multimodal integration of the sensing from multiple physiological systems was a stepping stone to the fruitful usage of health and behavioral analytics in the USAF. Human analytics of this trove of information would be an untenable proposition, but AI has recently shown great success in exploiting such big data (in fact, data richness and density is a precondition to usefulness in AI). There is an important caveat that essential information might be missing in adversarial contexts (e.g. no direct sensing from the adversaries to which warfighters’ physiological states tightly depend). Nonetheless, based on a recent history of AI’s application to consumer behavior by the likes of Amazon, Google, Apple and Facebook, it is probable that, once connected to a dense web of input data, intelligent algorithms will deliver insights into the complex organization of human psychophysiology. Those insights may or may not be interpretable (Hassabis, 2017; Gunning, 2017; Sukkerd, 2018), but prior experience in consumer behavior suggests that they will be actionable. Because density of input data is key to training those algorithms (Wang, 2012; Sun, 2018), the structured environment of USAF could be a fruitful environement for this approach, with the benefit of improved operational levels and better management of human resources, just like psychometric testing transformed enrollment and contributed to efficiency one century ago (Terman, 1918).

State of the art: USAF personnel receive health, cognitive and behavioral testing at numerous points during their service. However, the testing is usually compartmentalized in their respective domains (“data silos” in AI parlance), are not mined for correlational insights, remain infrequent from the standpoint of the fast timescale of many psycho-physiological processes.

Goal: In 2030, USAF personnel will participate in health and behavior analytics using environmental and wearable sensors that will unobtrusively and securely connect to a central AI command system. The deployment of invasive technologies will also be considered under the specification of safe and ethical use (see next section). Two paradigms will be implemented. (1) In the first stage to be rolled out, data are mined by intelligent algorithms for the purposes of description and forecast. Those predictive analytic algorithms identify correlations and causal relations (e.g. one aspect of physiology, glucose metabolism, leading to psychological and cognitive consequences, e.g. degradation of vigilance). They suggest ways to optimize performance, guiding command for the enhanced allocation of resources. (2) In the second paradigm (closed-loop autonomous systems), humans are equipped with control system algorithms that provide with real-time interventions according to domain-specific models of regulation (see Potter, 2014; El Hady, 2016; Zrenner, 2016 for well-developed concepts in neurophysiology), for instance providing pharmaceutical or nutraceutical delivery under physiological demand as quantified by continuous data monitoring. Such interventions will be especially worthy in extreme environment and demanding operational conditions. Closed-loop systems embody the stage of autonomy that fully realize the integration of human and technology at the level of the single individuals.

***Vignette:* Iron Man in the Air**

Theme/Recommendation: Integrated Cognition
Captain Riley is in the control tower. She observes the planes returning from their intelligence mission in the distance and turns her attention to the controls and personnel before her. To communicate with the pilots, she looks out the window at their craft, and her sub-vocal speech is automatically directed to their headsets – “All clear for normal landing,” she sub-vocally instructs, and the pilots arrange their craft for sequenced landing. She turns her attention to a different set of controls monitoring the air field, ensuring all personnel are ready. A message light up on the monitor with standard instructions for the field crew. When the commander looks at the message and nods, it lights up green, and she says aloud, “yes”. The message is relayed to the airfield. The exercise continues without a hitch, with Commander Riley executing the Observe, Orient, Decide and Act (OODA) loop with seamless integration with her team and her equipment. The communications are made seamless because, in part, her intent is read directly from her brain signals, communicated out to the networked system via microelectrodes at the nape of her neck. Because the system is trained in the team’s task, there is also no need to specify the recipients of her message or to ask for options, or to work with a touch screen or other physical device. The technology also ensures accuracy in her response and reactions at a time of an emergency. Pilots have the same accessibility to their controls; by turning their attention to certain instruments, by communicating seamlessly with ground control for information, by making a decision and confirming it with a nod or a ‘yes’, their intended actions are carried out. This is human-machine teaming carried out to its most efficient ends.

d. Overarching issues: safety, security and self-determination

Description: Ethical issues associated with the AI acceleration are treated throughout this report. Here, we focus on the issues associated with technology-mediated augmentation of single individuals. Historically, many augmentations (e.g., vision-corrective glasses, steroids, plastic surgery) and implants (e.g., insulin pumps, cochlear implants, hip prosthesis) are broadly accepted by segments of society. For new technologies however, there remain foreseeable and unforeseeable challenges to monitor. The first challenge is to ensure that the USAF workforce’s safety from potential risks associated with those technologies is an absolute priority. Many invasive electronic implants (e.g. nanomachines, electrodes) have some risks associated with the body’s reaction to what it considers a foreign body (Anderson, 2008), including inflammation (Skousen, 2015), glial response in the brain (Salatino, 2017), and, when ports are present linking the inside and outside of the body, their recurrent risk of infection (Peramo, 2010). Surgeries to perform implantation, depending on their nature, also present small to significant risks (Mangram, 1977). As for non-invasive technologies, they likely have psychosocial risks as well (Leszczynski, 2015). The second challenge is to secure those technologies from hostile takeover and reprogramming (Leavitt, 2010; Frenger, 2013; Pycroft, 2016), which could also compromise the safety of their owners, let alone their operational effectiveness. The third challenge is informed consent (see also Yuste, 2017) from the individuals that are subjected to them. It is likely that performance-enhancing technologies will appeal to some of USAF personnel, thereby exerting undesirable individual and social pressure to adoption that might negatively impact all personnel. A fourth challenge concerns agency and the sense of self (Klein, 2016; Yuste, 2017). Feeling of being in control of one's action and destiny is integral to sustained mental health and performance (Karasek, 1979), therefore, any technology that potentially interacts with agency should be monitored for possible short- or long-term effects on mental health. In parallel, some neurotechnologies could have emotional and personality side-effects, either directly, or by way of a perception of being different due to the augmentation (Parens, 2014; Yuste, 2017). Perceived personality changes by the subjected individuals or their relatives, will have complex and far-reaching consequences on mental health, willingness and broader adoption of those technologies.

State of the art: Bio- and neuro-ethics have emerged as a key specialty in parallel with the development of augmentation and neuro-technologies. Most institutions concerned with neuromodulation or behavioral control have implemented ethics committees to envision the necessary adjustments to accompany research and adoption of bio- and neuro-technologies.

Goal: The USAF of 2030 should identify and implement a bioethics structure for the implementation and continuous monitoring of augmentation technologies. Additionally, there is no guarantee that adversaries will follow the same ethical and moral guidelines that the US traditionally holds. Thus, is it critical that USAF invests in both research and intelligence resources into (1) understanding the development of these technologies and (2) defense against unethical systems that adversaries will have adopted, contrary to USAF and ethical guidelines and laws. USAF will develop intelligence signatures for these capabilities and be able to track their use in the field.

II. HUMAN MACHINE TEAMING

The interaction between human and machine is in rapid flux, and this socio-technological transformation needs to be rapidly conquered by the USAF to preserve its operational edge. Therefore, emerging opportunities for a merger of human with technology, as well as the increasing deployment of autonomous machines (section 3) require a new formalism of Human-Machine Teaming. This requirement is reflected in US Defense doctrine which posits that human-machine teaming is an essential element of the Third Offset Strategy – a Pentagon directive to offset the advantages of potential adversaries through innovative technologies (Hagel, 2014; Work, 2015). This section examines the socio-cognitive and organizational implications that arise from these novel forms of interaction and provides exemplary forms for each of them. In some cases, Human and Machine strive toward a single, shared goal with *a priori* well-defined roles. We will designate those under the label "integrated cognition" and behavior. In other cases, human and machine operate with distinct goals or without strictly predefined roles. In some of those other cases, traditional theories of human teamwork will directly apply. But at other times, because of disruptive changes and opportunities into the Air Force's mission structure, new conceptions of human-machine teaming will be required. These novel forms of teamwork will need to be studied together with advances in technology.

"Integrated cognition" and collaborative cognition (to follow in this section) live on a continuum. For example, the concept of "centaur" (born from chess master Garry Kasparov at the outcome of its surrender to supercomputer Deeper Blue in 1997) represents an intermediate point that highlights how machines might complement humans rather than replacing or merging with them (Scharre, 2016; Kasparov, 2017). The "centaur" concept evolved from chess AI research to describe a new entity: not simply a human playing a machine, or even machines playing each other, but in fact, a human-machine chess team (half computational "knight", half human) playing another opponent. This concept leveraged the superior capabilities of each partner: speed and information processing capacity of machine intelligence with integrative and innovative thinking of humans, the latter retaining the decisional power of which move to implement. While machines could routinely beat human opponents, human-machine chess teams could beat the computer operating alone (Cowen, 2013). This combination of human and computer nicknamed intelligence amplification (IA) vastly expanded the mission space, with more complex forms of planning, decision making, and problem-solving (that is, higher level cognition) than would be feasible with either partner alone. Interestingly, with a subsequent AI challenge with the Chinese game of Go (a complex strategy game with much deeper search space than Chess), a professional player and European champion, beaten by a distributed computing infrastructure and its algorithm DeepMind (Silver, 2016 & 2017), significantly increased his world ranking after practicing his game with the algorithm (Shead, 2016). This suggests that human-machine teaming also expands human cognition.

In examples of integrated cognition, human and machine have well-defined roles. For instance, in Centaur chess, the machine filters vast amount of information (opening and potential moves) and funnels it to a human decision maker. In other such examples of integrated cognition, it is machine cognition that is supported, with human intervention at intermediate stages of either machine training or automated decision process. The human contributes knowledge that the algorithm has no access to, and (s)he discards irrelevant pieces of information (Karanasiou, 2017; Prevot, 2010; Roth, 2004). This approach has been applied in medical decision making: for example, in (Awasthi, 2014), an algorithm used limited human supervision to cluster data in a certain number of groups, soliciting human input as to whether it should split or merge some of them. Machines, in no small degree, can generate enormous amounts of information on the successive states of a deterministic system. To this day and thanks to a rapid fall of the cost of computing elements combined with convolutional neural networks, machines have made tremendous progress in autonomous perception and cognition (recent review in Hassabis, 2017). However, they remain somewhat limited in their ability to effectively use that information: the big challenge of general AI. This is especially true in real world contexts with complex and changing goals to simultaneously manipulate. Therefore, aspects of human-machine teaming that remain the *forte* of human cognition at the time of this writing are capabilities to identify what might be the relevant information (Endsley, 1995), how to integrate this information and how to adapt thought processes for some current purpose. Naturally, with distinct skills and abilities, the question of teamwork is streamlined to which aspects of a task each agent, human and machine, is most proficient at.

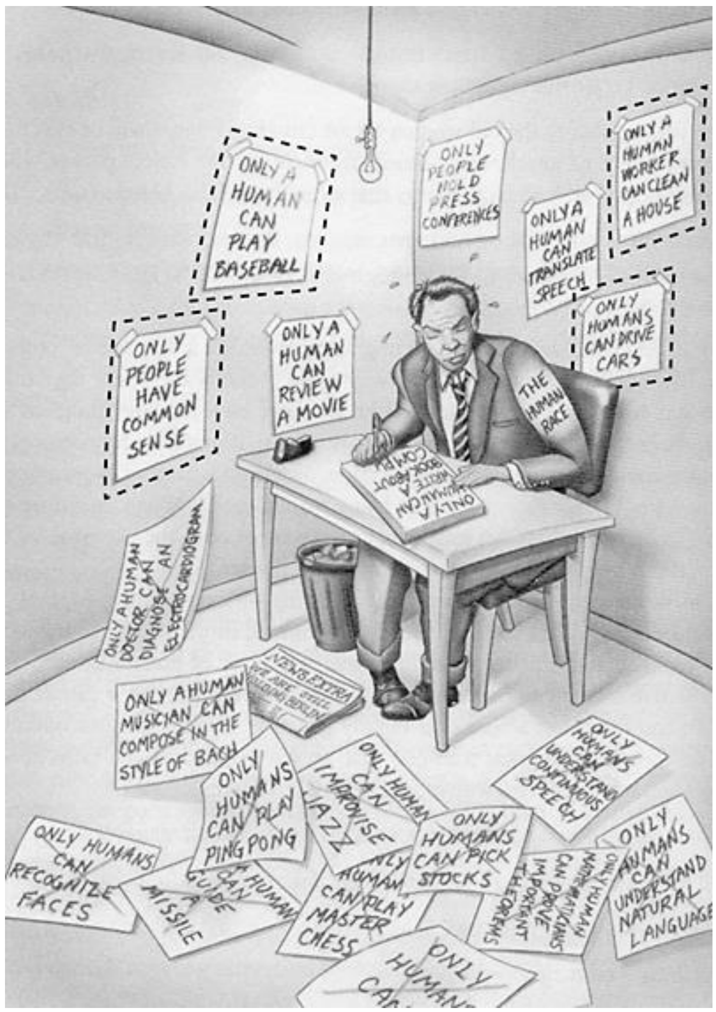

Figure 8: AI overtaking human skills (Image courtesy of Ray Kurzweil).

This situation is evolving with Machines developing autonomy and agency, and with Artificial Intelligence rapidly conquering news skills. On many of those other cases, skill sets do not clearly part human and machines with well-defined capabilities, or the roles change dynamically over the course of task performance. Those aspects of human-machine teaming will often conform to the literature of teamwork. An important distinction was made between taskwork and teamwork (Salas, Dickinson, Tannenbaum, & Converse, 1992). ‘Taskwork’ describes individual and collective activities that are pertinent to achieving the goals and objectives for which the team is formed. 'Teamwork' describes the activities involved in interacting with team members that are necessary for success. Said another way, taskwork refers to what needs to be accomplished to meet goals and complete objectives, that is, this is the "work" of human-machine teams. This includes a need for both the human and the machine team members to form an understanding of the relevant goals and objectives; be able to use resources in service of objectives; and engage in actions such as conducting analyses and interpreting incoming data and information. The teamwork construct refers to the factors required to function effectively as part of an interdependent team. This encompasses attitudinal factors, for example, emotion and attitudes arising from working with teammates (e.g., trust). There are behavioral factors, skills supporting interactions with teammates (e.g., communication). Finally, there are also cognitive factors that are associated with teamwork. This includes knowledge associated with teammates such as their roles and responsibilities as well as the particular level of expertise they might have. By analogy to Human-Human collaboration, successful Human-Machine teaming will need teamwork processes to be grounded in suitable models of machine cognition, and/or to emerge in the interaction. In the following, several avenues for this implementation will be outlined.

Finally, the conceptual framework of interdependencies helps to anticipate the level of demand imposed on human-machine teamwork. Interdependencies describes *who relies on whom* for task completion and how does that alter collaboration (Fiore, 2008; Saavedra, 1993). Pooled interdependence is where each teammate performs his/her own task, and the team result is the sum of each member's output. It imposes minimal demand on teamwork. Sequential interdependence occurs when one teammate's output is necessary for another teammate's input (i.e., B cannot act without output from A). In reciprocal interdependence, one teammate's output becomes another teammate's input and vice versa. Last, intensive interdependence is the highest form of coordinated activity – teammates "jointly diagnose, problem solve, and collaborate to complete a task" (Saavedra, 1993). These four classes provide a form of heuristic scaffolding to guide our understanding of coordination within human-machine technologies.

a. Teaming between Human and Embodied Machines.

Description: Articulated in the 1980s, Moravec's paradox (e.g., Moravec, 2009) stressed that locomotor and perceptual tasks that humans find most natural to execute (say, a child climbing the steep slope of a hill or recognizing her father's face) are prohibitively complex for even the most sophisticated robots, whereas high level cognition, such as mathematical computations or the solving of logics puzzle, finds the computer outdoing humans hands-down in speed and accuracy. Since this paradox was formulated, artificial perception has moved past this curse to some extent, but locomotion in embodied machines (robot, rovers), still faces those challenges. Consequently, there remains progress to be had before human and humanoid robot broadly share the USAF workplace (Barnes, 2016). However, there are specialties applications in which (generally non-humanoid) robots have already become pervasive, for instance the manufacture floors or medical environments (Wilcox, 2012; Alaiad, 2013), with teamwork based on collaboration or human supervision (Heard, 2018).

Based on meticulous study of human human-team coordination with nonverbal and verbal cues (Shah, 2010) and other aspect of human teamwork, much effort has been devoted to inferring human intent (Hoare, 2010) or other non-verbal cues (Loper, 2009) and endowing robots with shared mental models during the planning phase (Nikolaidis, 2012), dynamic task allocation (Few, 2006), implicit and explicit communication skills (Teo, 2018) or other socio-cognitive skills

(Wiltshire, Warta, Barber, & Fiore, 2017; Piçarra, 2016), so that robots can adapt to human preference (Wilcox, 2012) and mind other human factors such as situational awareness (Gombolay, 2017) to reduce human idling (Shah, 2011) and human mental workload (Gombolay, 2017; Heard, 2018; Teo, 2018) and improve human-robot teamwork performance. Other research has examined the factors that affect human perception of robot's participation in teams, and corresponding human behavioral choices in the interaction (Hancock, 2011), whose principal outcome is that robot performance and attributes are the major contributors to human trust, with environmental factors only playing a modulating role (Hancock, 2011). Yet other research has modeled how degraded communication channels between human and robot affect teamwork and changes the cost-benefit of machine's reliance on human command (Young, 2018).

State of the art: Robots have historically used predefined and inflexible action plans, but they increasingly rely on human socio-cognitive skills in teamwork with humans. The framework of Unified Theory of Acceptance and Use of Technology (UTAUT) has been employed to quantify the likelihood of people to work with robots (Alaiad, 2013; Dunstan, 2014) and the aesthetic and socio-cognitive factors that promote such willingness to interact. On the other side of already adopted technology, the above-mentioned laboratory progress in robot's socio-cognitive skills is progressively deployed in Human-Robots Environments, so that people engaged in teamwork with robots benefit from improved working condition, minimize workload and negative perception of the collaborative or supervisory interaction with robots.

Goal: In 2030, the USAF will increasingly develop human robot interactions that support its operational goals in air and space and its logistics and command on the ground. Before adoption, proposed technologies will be carefully vetted for their ability to support teamwork.

The allocation of teamwork will be dynamic and inspired from human interactions, with robots having technological enhancements that make them socially-competent.

b. Human-Computer Interactions and Co-Adaptation.

Description: Early on, ergonomics was not a focal point of human-machine interaction. But it quickly emerged that machines needed to work harmoniously and intuitively with their users, limiting the time required to learn to use them and increasing the spectrum of users (young, old, from a range of socio-demographic backgrounds). A primitive sense of teamwork was born. Since then, and similar to embodied machines, the broader range of "cyber" human-machine interactions (HMI) systems has made large gains in "social competencies". But unlike embodied machines, which retain a disadvantage in cognitive and behavioral agility before the human, cyber HMIs have come to take some leading roles in the accomplishment of shared goals with the human. This is in stark contrast with a traditional model that conceptualized machines as tools or, more recently, as assistants (e.g., Apple's Siri, Google Home, or Amazon's Alexa digital assistants). Recent advances in autonomy are the specific driver that challenge these traditional notions. For example, the Los Angeles Metro system field-tested an intelligent computerized dispatcher for security personnel (Delle Fave, 2014). It used game theory and real-time sensing to autonomously issue commands to human security patrols, and randomization to ensure police patrols were unpredictable (even to the police themselves). The technology had several benefits. Optimization techniques ensured that limited personnel were

Vignette: **Organizational Culture Implications of Warfighter Augmentation**

Theme/Recommendation: Communicating Ethics to Squadrons
It is promotion season and Colonel Scott is struggling to be fair to his team. The number of missions flown, in person and remotely, is so disparate, though each individual has worked with equal enthusiasm, patriotism, and professionalism. He can count on every one of the men and women on his team to do their job perfectly. Despite the differences in their performance due to innate ability and different Air Force-supplied cognitive and physical augmentations, their trust in each other is complete. Exercises and training has resulted in a team with good cohesion, despite the opportunity for soured interactions due to differing assignments and a number of synthetic teammates. He laughs, at least he doesn't have to worry about promoting the AI's!

Colonel Scott has handled the management of his team well, though it has been challenging to be fair. Unfortunately, guidance on promotions has been scant in this new context, and the old rules don't seem to apply fairly. He wonders, how can a leader determine who on their team is the highest performing, while accounting for disparate augmentations? Should they be accounted for? There isn't even a box for that on the already jargon filled form! How can he avoid granting a promotion that negates the good done by the augmented cognition? The enhanced skill, gained a great expense from the Air Force, may only be practical in the airman's current job - should this be taken into account as well, and does that mean that an airman is denied a promotion due to a job well done? Colonel Scott sighs and starts again through the promotion files on his laptop...

most effectively utilized. By incorporating information about train delays or security reports, the approach allowed patrols to rapidly adjust to changing circumstances. However, the approach was ultimately rejected as officers felt it impinged on their own sense of agency.

Such examples illustrate the potential but also the challenges in transitioning machine from tools to partners. Most human activity arises from partnerships between autonomous but interdependent minds. Heretofore, automated systems were incapable of acting as partners or teammates – they were mere tools (albeit very complex tools) that followed scripts on behalf of some human *operator* and stopped or failed in the presence of unplanned-for situations (Frost, 2006). In contrast, an autonomous system (IBM, 2005; de Lemos, 2013; Arcaini, 2015) makes choices on its own, even when encountering uncertain or unanticipated events. Autonomous systems often learn from their mistakes and change their behavior over time. Autonomous systems have their own beliefs and goals, and these might diverge from the people they collaborate with. Such autonomy enables far more complex relationships between humans and machines.

Lastly, in the wake of the influential MAPE-K model from IBM aimed at endowing machine with self-adaptive behavior (Garlan, 2002; IBM, 2006; de Lemos, 2013; Arcaini, 2015), an era developed when autonomy was pushed to a fault, avoiding human involvement at any cost wherever possible. Recently however, there is a growing undercurrent to return the Human-in-the-Loop (de Lemos, 2013; Camara, 2015; Lloyd, 2017). This new scheme no longer has human as a rescuer of things gone awry, rather, the human is truly becoming a partner in shared tasks. This further development into co-adaptive software recognizes that once systems have built sufficient self-reliance, they further benefit from knowing their limit, their inability to cope with high degree of uncertainty, and they pre-emptively know how to ask humans for goal-oriented help (intelligent teamwork). From a software engineering perspective, a major application of "human-in-the-loop" is in dealing with uncertainty, something at which humans excel, and machines regularly fail (Ruff, 2002; Holzinger, 2016). In co-adaptation (Lloyd, 2017), the system has a rudimentary form of a theory of mind and models self and humans associated with it toward shared tasks (understands self-capabilities, monitors environment and its uncertainty, keeps tab of each human performance history in specific tasks, human availability and motivation). Whenever the system model indicates self-sufficiently, it operates without humans. If the environment imposes strong uncertainty, and past experience and immediate context indicate that a human would outperform the autonomous system, then it intrudes and recruits for a human-in-the-loop. Those advances illustrate the dynamics of shared task performance between human and cyber HMIs.

State of the art: Cyber Human-Machine and Human-Computer interaction systems are increasingly connected (e.g. the Internet-of-Things, Bennaceur, 2016), acquire a growing amount of information on their embedding environment and their users, and parallelly, quickly accrue the skills to develop autonomous behavior (Garlan, 2002; de Lemos, 2013): the ability to pursue goals without Human-in-the-Loop. At the same time, there are other concepts under development to propel Human-Machine interaction into genuine form of intelligent teamwork.

Goal: In the USAF of 2030, more advanced machines will have their own goals, sometimes at cross purposes to the human members of a team. This includes examples where the machine prioritizes mission goals differently (much like in human teams), and mission completion requires a negotiation over how to reconcile these different perspectives. Such negotiation will be supported by “explainable AI”, forms of Artificial Intelligence that have developed the ability to communicate choices and values to elucidate the main elements leading to machine decision (Gunning, 2017; Hassabis, 2017; Wachter, 2017; Sukkerd, 2018, see also, Lomas, 2012); and progress in Natural Language Processing (Manning, 2014; Kumar 2016). Indeed, negotiation will generalize for intelligent human-machine interaction, supplanting the current master-slave framework. Just as humans play several distinct roles in human organizations, the USAF will harbor human-machine teams that expresses the full spectrum of relationships to maximize operational capabilities. The USAF will use sociological research to support this delicate organizational transformation moving machines from the lowest rung of its organizational hierarchy, to the status of peers and even leaders, with focus on organizational goal and performance, and with care to retain human adhesion to its collective goals. Further research will examine if technology affords innovative organizational relationships. For example, an autopilot might assume command of a mission under limited circumstances, but more generally, autonomy might allow organizational structures to dynamically change (re-tasking units to other air wings or even redistributing them across coalition partners) as an operation unfolds.

c. Cognitive Aiding: Intelligent Cyber Sand Tables.

Description: As the operational environment of the USAF becomes more complex, there grows a cognitive strain into global understanding that is crucial for leadership and strategy (Lintern, 2006; Grier, 2012; Kingston, 2014). Especially, leaders and decision makers at all levels need to examine and cognitively manipulate increasingly large amounts of data and facts (Kingston, 2014) in informational forms (Dubaz, 2016) and in cyber environments (Cook 2003). Aristotle and his contemporaries already recognized the profound entanglement of memory and spatial processing, imagining mnemonic techniques (method of loci) that serialized information in rooms to be mentally travelled (see also Burgess, 2002; Bird, 2008 for neurophysiological foundations). Throughout history, military leaders have used static sand tables as support for global awareness in accurate spatial contexts (Dubaz, 2016). As cognitive aids to the mental efforts of strategic leaderships, the expert panel suggested immersive and augmented virtual environments (see also Stanney, 2016) serving the routine inspection of cyber-spaces mapping physical and informational resources from the USAF and the cyber-space it contains or interacts with. For instance, aircrafts and information network resources of a squadron could be inspected every day by its captain in the form of a miniature, geospatially modeled virtual space, with augmented information signaling operational readiness of its components (aircraft colorized to signal function and malfunction, arrows to describe network integrity and information volume). Those novel technologies could support the cognitive decision making performed by USAF leadership. Further, those virtual systems could be endowed with autonomy, seeking and discovering meaningful information out of its pre-programmed architecture, and offering triaging, thereby attenuating the data deluge that has proved so harmful for human decision making (Kingston, 2014)

Figure 9: Virtual Sand tables could be enhanced with Artificial Intelligence (Image from: Herrmann, 2018).

State of the Art: Several enabling technologies have matured to support this new technology of intelligent and autonomous virtual sand tables. Virtual and augmented reality have started to be more widely used (Rheingold, 1991; Earnshaw, 2014; Barfield, 2015; Billinghurst, 2015; and section 5.II). Virtual Sand Tables developed both in service of military strategy and geospatial monitoring of critical ecological environments have increasing realism and functionality (Jung, 2008; Amburn, 2015, Herrmann, 2018; see also Wisher, 2001), if not intelligence and autonomy. On the other side of the problem, the growth of autonomy in logistic systems (Kowalski, 2012; Gunasekaran, 2014; Bordawekar, 2017) and the development of machine intelligence's ability to collect and utilize large amount of information once the data silos are broken and set into clouds (DHL/IBM, 2018) support further enhancements of those virtual sand tables from inert geospatial objects to truly intelligent agents cognitively aiding human decision makers. Finally, there is an increasing understanding from cognitive psychology of the multisensory, cognitive and behavioral factors that support memory and decision making (Baddeley, 1997; Zachs, 2000; Süß, 2002; Endsley, 1995; Klein, 2008). All of those developments are at the crossroad of the envisioned technological innovation of intelligent cyber sand tables.

Goals: In 2030, the USAF will adopt intelligent geospatial modeling for its virtual, informational and organizational spaces. The system~~s~~ will integrate its users' habits and preferences, anticipate needs and continuously refine its ability to discover and triage information to protect its user from overload. It will offer a rich multisensory experience in support of human information processing, learning, anomaly detection and decision making. This set of intelligent tools are likely to enhance military cognitive readiness (Grier, 2012) and aid in the daily consolidation and memory manipulation of important operational information (Fiore & Wiltshire, 2016).

***Vignette:* The "Cyber" Matrix**

Theme/Recommendation: Collaborative Cognition, Teamwork, Interdependencies
On Captain Chase's left, a steady stream of goldfish swim past, through the air, circling between two brightly lit lamp posts. On his right, an occasional green flash travels in either direction across an old-fashioned telephone line. All is normal in this neighborhood of the network. Messages between the control tower and air field circulate at their usual rate and with expected content, represented by the glittering goldfish. Less frequent communications between the air base and the army base 500 kilometers away are shown as individual flashes of light. Captain Chase "walks" this neighborhood every morning, checking that all is well. It has taken little time for him to understand the nature of 'normal' functioning in this network, due to its clear representation in this virtual reality, where communications among and within the various nodes are represented as sensory experiences reflecting his preferences and sensory strengths. Captain Chase strolls past the fish and the telephone poles to a miniature version of the airfield, where 11 miniature F-16s glow a soft green. The twelfth, however, glows yellow, an indication that its communications link with the other planes or the control tower is experiencing delays. He transports to take a closer look, and confirms the nature of the problem by gesturing to move the miniatures around on the field. He lets the flight maintenance crew know that the last F-16 needs a software update, confident that the latest patch will solve the problem. Later when he strolls by a second time, having checked on everything from the Air Force personnel's personal communications devices to the health of encrypted message systems, he returns to the miniature flight deck to find all 12 planes glowing green again.

d. Cognitive Assistance: Expert Digital Systems.

Description: Digital assistants like Apple's Siri, Google Assistant, Amazon's Alexa and Microsoft Cortana and other more specialized chatbots have brought pervasive conversational intelligence and unprecedentedly fast access to a cloud-based knowledge that expedites access to information and identification of operational answers (Abdul-Kader, 2015; Serban, 2017; Henderson, 2017; Ciechanowski, 2018). They seamlessly interact with humans thanks to their mastery of natural language (Henderson, 2017; Green, 2015). Their immense benefit, in this 21st century of information, lies with the time they spare from human searching painstakingly for information that they discover and deliver in matters of seconds (Mehr, 2017; GAO, 2018). A growing number of major companies have embraced those artificial intelligent agents to augment their agility (DHL/IBM, 2018), and have shouldered the cost of the initially high investment to transform their organizational structures (DHL/IBM, 2018; see National Research Council, 2014, for similar thought process aimed at Information Technologies in military operation). Due to the sensitive nature of its information and the inherent risk to widely network it, a similar data warehouse for artificial intelligence in USAF operation has to be built with total separation from the web-based civilian systems and endowed with strong security (Wang, 2015). However, a specialized expert digital system for USAF could retain institutional culture and knowledge and greatly aid in operations at all levels. Personnel turnover would be mitigated by a machine-based retention of knowledge about 'who', 'where', 'what' and 'when' each operational task concerns (Kowalski, 2012). Whereas office workers spend great amount of time to search information (Mehr, 2017; DHL/IBM, 2018), this time cost would greatly diminish, releasing workers' ability to attend to the information and perform higher-level cognitive tasks such as deciding and planning.

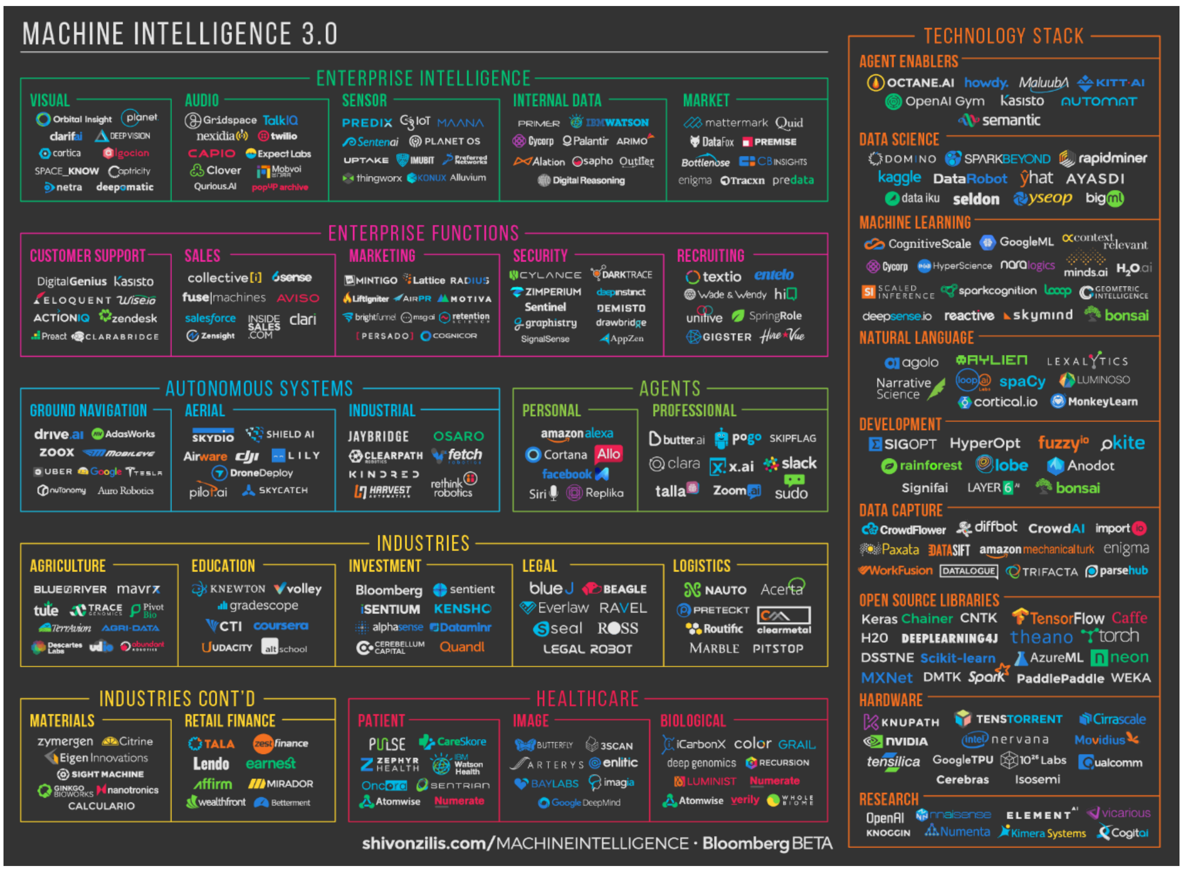

Figure 10: The AI landscape, 2016, by Shivon Zilis (http://www.shivonzilis.com)

State of the art: A handful of companies, many in the United States, have honed the leadership in data analytics with artificial intelligence and machine learning. Implementation requires the retrospective and prospective collection, migration, validation, curation and organization of data, often under the oversight of a data architect and sometimes with other intelligent technology developed specifically for this purpose (Zaharia, 2017). Adoption of Artificial Intelligence requires a large early investment (DHL/IBM, 2018), but affords the derivative advantage that collected data serves numerous purposes in the organization. It also supports "intelligence analytics", the internal quantitative study of organizational performance, and organizes Information Systems and Information Technologies more efficiently. The data can also lend itself to simulation (Fawkes, 2017 for specific military application).

Goal: By 2030, the USAF will have realized its infrastructure transformation for data intelligence, and all personnel will have structured access to expert digital systems that offer knowledge support for operational tasks. While setting up this expert digital system, USAF will have broken its data silos and will accrue data collection on personnel, tasks and logistics. This transformation will reduce response time and error rate in all operational tasks. It will deliver increased understanding of organizational effectiveness and guide leadership in decision making.

e. Overarching issues: organizational structure, social justice, trust, agency and privacy.

Description: These new conceptions of human-machine teaming are likely to introduce disruptive changes to the Air Force's organizational structure, how it conceives of and handles its operational domains, and more broadly, the character of military culture. For example, machinery has traditionally performed routine tasks at the lowest rungs in an organizational hierarchy, thereby creating little disruption to the remaining human elements. But as machines become more able to take on critical mission responsibilities and make their own decisions, new forms of command and control may be required. One obvious consequence is the need to transition commanders from "human-in-the-loop" decision-making to "human-on-the-loop" decision-making wherein commanders retain overall command but delegate control to autonomy (David, 2016). But more controversial situations may be required to achieve operational goals, such as having an implant temporarily take control over a warfighter's body to save his life, or human teammates receiving orders from a machine intelligence. Though these changes may be profound, existing research on human teams and organizations provides a good starting point to explore the implications of human-machine teaming.

State of the Art: This research has identified several important processes underlying effective teamwork and multidisciplinary research is needed to translate these concepts into the realm of human-machine teams. These new conceptions may challenge traditional human notions of ethics (Russell, 2015; Conitzer,2017), privacy (Vaidhyanathan, 2014) including collective forms of data protection (Pagallo, 2017), agency (Thürmel, 2014), justice (Rissland, 1990), social standards and autonomy.

Goals: Leading into 2030, the USAF will carefully prepare adoption of artificial intelligence, its trust by USAF personnel and in the broader US society, paying attention to potential barriers for acceptation of this new technology, and seeking a consensus on the scope and limit of machine autonomy. USAF will ensure that autonomous and collaborative machines endowed with agency behave ethically with partners and adversaries and develop social cognition to enhance human-machine teaming. Hybrid human and machines teams will jointly retain the responsibility of analyzing their team effectiveness and steering their team- and task-work in ways that increase operational goal performance in agreement with shared values (Schwartz, 2012). The questions of accountability for performance and failure will be monitored over the early phase of human-machine teaming deployment and beyond.

III. FUNCTION AND DYSFUNCTION OF AUGMENTED HUMAN-MACHINE SYSTEMS

Technology-enhanced Human-Machine elements will be a completely new entity within the Air Force's capability set. One of the largest consideration (and barrier to adoption) of these new technologies is the lack of understanding of the full capabilities and conditions under which these new systems operate. The novel organizational structure introduced by a pervasive AI-accelerated human-machine teaming will require meticulous monitoring, to adjust operational settings to constantly learn and improve, to correct for emerging defects, and to estimate over multiple timescales its ability to support USAF mission. There is also a need to examine the vulnerabilities of human-machine systems, both from the perspective of defending against enemy attack but also with the aim of degrading the capabilities of adversary human-machine systems.

a. Evaluations of Human-Machine Performance toward Mission Objectives.

Description: Research and capabilities in the commercial domain (Makridakis, 2017) suggest that AI accelerated technologies and human machine teams will operate with enhanced efficacy within expanded mission sets. Given that, it is critical to create a test and evaluation framework for these new capabilities. Although it is complicated and oftentimes perplexing to identify the best methods for evaluating a new technology or enhanced capability, several directions can be suggested that integrate with the organizational structure of the USAF. Since these technologies will not be employed equally and evenly across the domains of air, space and cyber, the evaluation framework will specifically examine how these new technologies will best optimize operations in each of them (table 2).

Technologies	Air	Space	Cyber
Cognitive and Physiological Augmentation (I.a)	✓	✓	
Neurotechnologies (I.b)	✓	✓	✓
Sensing and Closed-Loop Systems (I.c)		✓	
Human-Robot Teaming (II.a)		✓	
Co-adaptive Human-Machine Interfaces (II.b)			✓
Intelligent Cyber Sand Tables (II.c)			✓
Expert Digital Systems (II.d)	✓	✓	✓
Hybrid Swarm teaming (autonomous and human)	✓		

Table 2: domains of evaluation for AI accelerated Human-Machine Teaming at the 2030 horizon

State of the Art: In normal military operations, human warfighters are trained and evaluated all the time. This routine of evaluation and performance introspection will form a useful basis for the assessment of Human-Machine technologies. Humans are autonomous systems themselves, though they have mechanisms of shared understanding that allow them to communicate intent, assess understanding, explain and correct errors, etc. Research has prototyped several approaches to accomplish this natural communication for human-machine entities as well (see explainable Artificial Intelligence in section II.d, and shared mental models in sections II.a-b above). The USAF also has a long history of successfully testing complex machines in extreme conditions. “Test Pilot” is a trusted mechanism for allowing the USAF to understand the limits and full capabilities of novel platforms.

Goals: By 2030, the USAF will develop and integrate a “Test Pilot” equivalent for human-machine teaming. This oversight acknowledges that newly developed systems expose the personnel of USAF to unknown risks due to *a priori* lack of knowledge of their strengths, weaknesses and limitations. AI and Augmented Cognition will not arrive to the battlespace fully formed. It will need to be understood, adapted and hardened for its full utility in the force. The commercial industry is facing noteworthy issues with the development of autonomous cars. While human-operated cars kill hundreds of individuals a day (WHO, 2018), seemingly more than autonomous vehicles (Blanco, 2016), autonomous cars are currently held to an impossible metric of “perfect” performance (Kalra, 2016; Hengstler, 2016). The industry is currently satisfying this social demand by training autonomous car with millions of miles of open-road testing. And yet, society still hands a moderately trained 16 years old human a driver’s license, and regards fatalities involving autonomous driving with intense scrutiny. To avoid similar conundrum, validation and verification of USAF deployed Human-Machine Technologies will involve baselining capabilities and exploring the environments and missions that most effectively use the new technologies. As it considers deploying technologies with increasing levels of machine intelligence, the Air Force will need to be a thought leader in the rigorous test and evaluation of these systems.

When planning a mission and objectives, commanders review the specific quantitative metrics associated with the resources they will draw upon (fighters, bombers, tankers, ranges, fuel consumption, etc.). For the complete employment of human machine elements, commanders will have to understand the full range of features that they contain, to make choice for a certain mission or function (which organizational structure should be used with these new capabilities? When should a human or humans be used without augmentation? When would one use a human machine team or a cyborg? How should it be decided? What are the pros/cons?). Additionally, if one is fighting an augmented adversary, advance intelligence, when available, will be factored in the planning to avoid being exposed to strategic surprise and corresponding operational loss. The analytical power of commanders might also be complemented with a big data/machine learning approach (McAfee, 2012) that would rely upon prior missions, agent-based modeling (Kozlowski, 2016, 2018), and Live Virtual Constructive (LVC) simulations (Varshney, 2011; Hodson, 2014). The overarching goal is the identification of the most effective operational configuration in support of missions. That mix will change based on who the USAF is fighting, how it is fighting it, and in which domain (Air, Space, Cyber).

Vignette: **Hacking Implants for Mind Control**

Theme/Recommendation: Centaurs, Levels of Cognition, Validation & Verification
Lieutenant Baron is looking forward to a productive day in his role as intelligence officer. He has performed weeks of training in this job and has a great handle on the adversary's profile. His training and his performance have been helped by INSIGHT, a brain enhancement that, while still experimental, has proven extremely useful. He is able to absorb and understand information very quickly, and to synthesize information from multiple domains in a way he has never before experienced. Working with a variety of external databases and information collections, Lieutenant Baron can access exactly the data he needs with incredible speed and accuracy – and he has never learned a line of code or how to formally query a database. Getting ready to start his shift, Lieutenant Baron must now perform a set of daily exercises to test the integrity of his implant. Because INSIGHT communicates with external systems, he must regularly verify that the communications link is secure and reliable. He looks at his wristwatch and chooses the tester, which communicates a series of logic puzzles, chosen randomly, to his brain. If he is able to correctly answer the riddles, the test will succeed – meaning the communications to and from his implant are reliable. Meanwhile, the automated tester attempts to send messages through several unauthenticated devices and means; each one of these messages is blocked, giving assurance to the Lieutenant that is thinking won't be impeded by any unexpected people or systems – whether inadvertent or intended. He's ready for the day and plugs into his intelligence system for his first tasks of the day.

b. Defense Systems for AI Accelerated Human-Machine Technologies.

Description: Information security is a complex and always evolving area (Burns, 2017). Taking brain networks as a well-studied inspiration for graph-theoretic complexity, it has emerged that connectivity is a double-edge sword that reduces distance and increases efficiency, but also forms the basis of great vulnerability (Bullmore, 2009): the stronger the connectivity, the greatest the risk. This is a reason why evolved biological complex systems usually have structured and weak connectivity patterns (Bassett, 2006; Whitacre, 2010). An obvious consequence of the greed of artificial intelligence for big data (Wang, 2012; Sun, 2018) and their networking (see also Baker, 2016) is its corollary vulnerability. Accordingly, there is a need to develop robust defense along with the installment of strongly connected infrastructures for AI acceleration.

In the networked data from an AI-accelerated USAF, compromised function can come from multiple origins, and requires different security measures. System dysfunction will be closely monitored (an even more intensely in early stage). Insider human error (Vieane, 2016) and intentional human corruption (Clarke, 2013) will require a combination of machine and human oversight. There are also risks coming from adversarial attacks (Korns, 2009) and the contamination from friendly entities whose own systems have been compromised. All those systems will need specialized yet integrated defense measures.

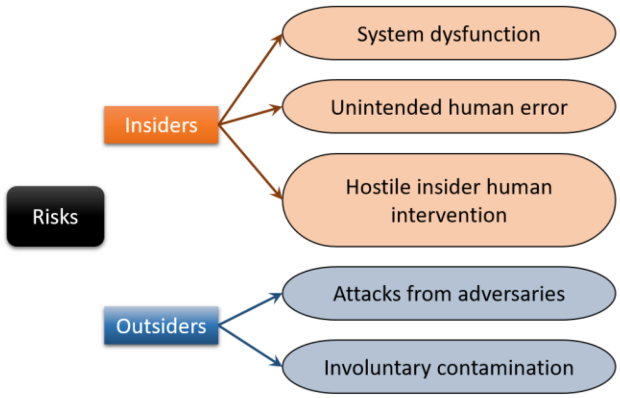

Figure 11: Risks to AI hypernetworks classified by origins

State of the Art: With its cyberspace operation and personnel, the USAF has foundations to address some of the above risks to cyber-protection. It has adapted the Intelligence Surveillance and Reconnaissance (ISR) concept to cyber space (Bush, 2013). It has built capabilities for electronic system monitoring, network defense and attack and exploitation, and system assessment (USAF, 2016). USAF also has a long tradition of cyber-defense exercises (Mullins, 2009, see also Schepens, 2002) that supports its understanding of the evolving area of cyber defense, while providing training to its personnel.

Goal: By 2030, USAF will deploy new tools to monitor its AI accelerated systems, and safeguard its information, its networks and communication channels, and the ancillary resources they rely on, including power (Adams, 2015). Those tools will combine human intervention and computer tools, including autonomous ones (Coldewey, 2016), and will secure personnel recognition with increasingly sophisticated biometrics. USAF will prepare response planning for catastrophic scenarios. It will also build damage assessment protocols (Grimaila, 2007) for rapid identification of the consequence of damage and attacks, and recovery monitoring protocols to track the restoration of functionality. It will constantly reevaluate its response plan, as adversaries and context will be everchanging (Burns, 2017). It will also deploy tactical deception for cyber-protection (Grant, 2010) and engage in collaborative cyber-defense with other DOD and friendly entities (Andress, 2013). The relevant expertise will be gathered from computer and network security (White, 2017), human factors (Knott, 2013) and artificial intelligence (Rehman, 2014; Russell, 2015) so that evolvability is ensured (Whitacre, 2010).

Vignette: Keeping Your Cool when Stakes are High

Theme/Recommendation: Forms of Conflict, Teamwork
Captains Russell and Cameron enter the SpaceBase break pod at the same moment, and both pause briefly. The smile on each space fighter's face vanishes, and a cold chill envelops the room. Captain Russell has just returned from a very pleasant conversation with his wife and kids. His interactions with them have been aided by Artificial Intelligence that helps overcome the awkwardness of the delay in communications experienced on all calls with earth, ever farther away. The predictive models of conversation have been customized to his relationships and speech style, and he has included some great stories and jokes for his kids. They have all gotten used to the special style of conversation afforded by this technology. For her part, Captain Cameron is ready to celebrate a job well done just moments ago. She accomplished a major fix on some of the station's weapons equipment. The AI that guided her in the process not only gave her step-by-step instructions, it also sensed when she felt stressed and overwhelmed, and helped her slow down, breathe deeply, and used instantaneous neuromodulation to lower her cortisol levels. With this help, the job was done before she expected, and she has time to relax. But now, the space fighters must interact, and these interactions have been strained in the past weeks. That is to be expected on this kind of mission, in such close quarters for extended time. Again, AI is able to help them. Captain Cameron heeds her internal team coach encouraging her to ask about Captain Russell's wife. He says she is well, and offers congratulations to Captain Cameron on a job well done. A tense moment is diffused, and each is able to relax in the pod lounge, feeling good about their day.

c. Offensive Cyber-Strategies Aimed at Human-Machine Technologies.

Description: Many nation-states and other actors big and small (terrorists, activists, cybercriminals and corporations) have developed capabilities for cyber warfare (Mazanec, 2009; Bush, 2013; Pomerleau, 2018). Facing a gap of international laws, and until such regulations are fully formed (see difficulties for a ban on cyberweapons in Shackelford, 2009), it is usually agreed by nations governed by the rule of law that legal basis for cyberwarfare, just like conventional war, concerns self-defense (provided that attribution can be successful, an especially difficult issue in cyber, see Mudrinich, 2012; Libicki, 2009b) and authorization from the UN security council (Kosina, 2012). Four classes of offensive means are (1) Cyber-Physical Systems, in which software instructions can impose damage on the critical physical resources at the end of an information system; (2) jamming information networks to paralyze physical resources, communication and financial systems, and deny adversary access to information; (3) viruses and cyber-intrusions aimed at gathering critical intelligence, disrupt opponents software, physical and financial resources and information; and (4) social bots exerting psychological and cultural war by manipulating people's opinion, which are rendered more effective by coordinated behavior. With the advent of Human-Machine technologies in adversaries, emerging offensive targets include soldiers (physio- or neuro-hacking, social influence on beliefs and trust), human-machine teams (create conflict, distrust and degrade communication), information (surveillance, corruption and destruction of AI servers and data warehouses) and machines (cyber-neutralization of robots, computers, unmanned vehicles, teleoperated systems).

State of the Art: Information is as precious a resource to modern societies as essential assets such as energy, food and water, a fact that was well recognized by numerous countries that have built strong cyberforce. This is because societies have become extremely dependent on cyber-systems at all levels. And it is critical to the AI-accelerated Human Machine Teaming described above. The USAF has a wing in charge of defensive and offensive cyber operations (USAF, 2016), and efforts are ongoing to increase coordination within DoD and with friendly nation-states. Application of cyber-offense to AI-accelerated Human-Machine Technologies tough is an emerging issue with little prior foundations.

Goal: By 2030, the USAF will develop offensive cyber-weapons addressing adversaries Human-Machine technologies, for deterrence (Libicki, 2009a) and self-defense. Those will include cyber-blackout (Adams, 2015), bots (Aro, 2016; Woolley, 2016; Oxford, 2016), viruses and intrusions. At the same time, the USAF might lead into the development of ethical international laws into cyberwarfare.

C. Research Questions

The team deliberated on many issues related to human-machine interactions and multiple possible scenarios therein worth considering. Following questions were brought by the team to be explored further. They are grouped for convenience below.

Questions related to Organizational and ethical implications of human-machine technologies

- Will operating through an autonomous robot increase risk-taking, reduce vigilance to threats and increase dehumanization of others? Or might it soften or even reverse these effects?
- What are the implications for power dynamics between humans when inserting autonomous machines into the organizational chain of command?
- How do machine teammates transform social and team norms? For example, might humans be more willing to criticize and/or accept criticism from a machine or would the opposite occur in that machines can potentially record and distribute this information across the chain of command?
- What methods of accountability are most effective when some decision-makers are machines?
- What are the analogues of social capital and team resilience when some team members are machines?
- Multi-disciplinary research is needed to examine the psychological, organizational and cultural impact of these advances.

Questions related to Trust in Autonomy

- What theoretical frameworks are appropriate to examine trust in autonomous machines? Will theories developed to study simple “automation” apply or are theories of human interpersonal trust more appropriate?

- Do these differences evaporate as machines become more autonomous (and, thus, should human-machine teams draw on the vast literature in organizational psychology?) or will human-machine teams transcend existing team paradigms and demand novel theoretical models?
- To what extent should machine teammates explicitly incorporate human-like elements (e.g., human form, voice) or will this create false affordances that undermine trust and/or place blinders on research that might lead to more transformative forms of interaction
- How do these issues change depending on the nature of human-machine interaction (e.g., integrated intelligence versus collaborative intelligence)?

Questions related to Shared Mental Models and Theory of Mind

- How will realization of theory of mind in artificial agents, that are members of human-machine teams, alter cognition and collaboration?
  - Does this facilitate communication across team members?
  - Does this facilitate understanding intent when such teams engage in complex cognitive processes like decision making and problem solving?
  - Does this foster the development of shared situation awareness in human-machine teams?
  - Does this influence the development of shared mental models in human-machine teams?

Questions related to Taskwork and Teamwork for Developing Human-Machine Teams

- **How to Promote Taskwork?**
  - Should the machine or human help articulate clear and precise goals?
  - Should the machine or human help maintain a collective focus?
  - Should the machine or human help coordinate in support of team interdependence?
  - Should the machine or human help seek member input?
  - Should the machine or human help plan future contingencies with members?

- **How to Promote Teamwork?**
  - Should the machine or human serve as a model of teamwork?
  - Should the machine or human help explain rationale for decisions?
  - Should the machine or human help create a supportive climate (e.g., trust)?
  - Should the machine or human help members gain self-efficacy?
  - Should the machine or human help collect performance information and provide feedback?

Questions related to Developing Human-Machine Teams for Dealing with Conflict

- How can human-machine team research better understand the support of TASK conflict? This includes making explicit knowledge diversity and encouraging discussion of evidence.
- How can human-machine team research better understand the management of relationship conflict? This includes how to manage emotional/attitudinal issues in the team (e.g., trust in technology).

- How can human-machine team research better understand the management of logistical conflict? This research includes how teams can develop awareness to better manage resources that are available as well as offer clear strategies on how to use these.
- How can human-machine team research better understand the management of contribution conflict? This research includes on how machine team members can better understand the team roles, objectives, and goals, as well as being able to make explicit each person’s role for the mission.

4. HUMANS

Figure 12: AI and its implications on humans (Photo credit: Classical Post; June 3, 2017).

A. Background and Current Status

People are integral components to success across all areas of the USAF's mission. By 2030, humans will continue to be centrally involved in USAF operations, from logistics to maintaining and controlling warfighting machines. At the same time, it is anticipated that the role of the Air Force personnel will change as engineering and technology-related breakthroughs occur.

It is essential to build an understanding of how to identify and recruit the next generation of Air Force personnel to align with changes in the USAF environment associated with advances in AI and augmented cognition. After recruitment, Air Force personnel must be prepared to tackle challenges of the future USAF that leverage AI and augmented cognition that maximizes training programs in the relevant skills. Therefore, understanding how to improve and maintain human performance is crucial in preparing for 2030 operations. The creation of modern human-linked technologies and other improved methods for training that support readiness, as well as mental and physical health, requires thorough research. In this report, we distinguish between "humans" and "human-machine integration/teaming" based upon the application of the technology to meet particular goals. Specifically, we categorize research areas as "human" when the goal is human development through training and general support services (e.g., mental health). This is distinguished from the use of technology where the goal is to augment human capabilities in the operational environment (e.g., “smart helmets” to monitor pilot workload), which would be considered “human-machine” research and development.

We highlight four themes within the area of Human-related research that are related to the lifecycle of personnel in the USAF:

I) Workforce Composition
II) Training the AF personnel of 2030
III) Health and Wellbeing
IV) Sustaining the Workforce and Quality of Life

There is a plethora of ethical, legal, and social considerations throughout all of the themes outlined below. While we do not outline our specific concerns, we support the ethical principles described in the appropriate federal guideline documents relating to the protection of human subjects in research.

B. USAF in 2030

I. WORKFORCE COMPOSITION

Figure 13: Changing workforce with the AI Advent (Photo credit: Villanova University).

The USAF of 2030 may look very different in terms of its workforce. The proliferation and integration of AI and augmented cognition technologies may change the type of recruits that the USAF typically inducts. Likewise, training for jobs in which personnel must routinely interact with and coordinate their activities with AI's introduces unique challenges. In this section, we discuss key considerations concerning workforce composition.

a. Workforce Readiness

Description: Advanced technologies, including AI and augmented cognition, will require a workforce competent in computer programming, engineering, and other fields from across science and the humanities. The same applies to the design and development, manufacturing, operation, sustainment, and in some cases, even retirement of these technologies. It touches every facet of Air Force operations from combat operations to logistical support. This need encompasses Air Force personnel and contract support staff, as well as private industry and research organizations supplying the Air Force with technical capabilities and supporting them before, during, and post-deployment.

State of the Art: The marketplace for personnel with an aptitude to excel and with knowledge and skills in STEM-related (Science, Technology, Engineering, and Math) fields is highly competitive, with commercial industry having many comparative advantages in the ability to recruit these individuals. Numerous DoD or USAF programs exist that seek to encourage and support STEM education within K-12 grades (e.g., DoD Starbase, 2012) and for post-secondary students (e.g., AFRL scholars program, Universities Space Research Association, n.d.). While it has proven easy to create interest in STEM subjects, especially at the K-5 level, programs have struggled to sustain that interest and translate it into an active, lifelong pursuit of STEM-related endeavors. Programs struggle to sustain participation in STEM-oriented activities as youth progress through middle and high school and undergraduate college, with this particularly true for girls (Chen, 2013). One other issue of relevance is the fact that a disproportionate amount of the STEM workforce is foreign-born (Lowell, 2010).[4] Another major issue is the glacial pace of change in universities; the curricula in mostly universities has hardly changed from 30 years ago.

Goal: STEM-oriented programs targeting the future technology needs of the Air Force that create an enduring engagement in and commitment to STEM pursuits with a broad cross-section of youth extending across levels of academic performance, gender, cultural background, and socioeconomic status, beginning at the K-5 level and sustained through the teenage years and early-adult post-secondary education. Finally, to have a workforce ready to achieve the goals outlined, there will need to be major changes in university curricula.

b. Role of USAF Personnel in 2030

Description: The job classifications and descriptions of personnel in the USAF will likely evolve at an accelerating rate as transformative technologies, engineering, and data advances create new jobs. Many of the jobs that will be critical to the success of the Air Force in 2030 may not

[4] Lowel (2010) asserts that the foreign-born or internationals make up one quarter of the workforce in the life and physical sciences, one fifth of information technology, and one sixth of the engineering workforce.

exist today. It will be pertinent for the USAF to anticipate what jobs may be on the horizon and begin planning, recruiting, and training Air Force personnel for these roles.

State of the Art: The USAF currently has defined job classifications and descriptions (Air Force Personnel Center, 2016, 2017; USAF, 2012, 2015).

Goals: As the Air Force integrates new software and hardware technologies, they, in turn, may necessitate new skill sets like predictive analytics, dataset curation, and new jobs such as autonomous vehicle trainer or AI maintainer. It may be integral to ongoing dominance in the Air, Cyber, and Space domains that the USAF identifies these roles as they emerge, focus recruitment on individuals with the knowledge and skills to excel in these jobs and establish corresponding training protocols.

c. Big Data Approach to Personnel Placement and Retention.

Description: Tremendous amounts of data may be collected and mined (e.g., data analytics, educational data mining) to identify the characteristics of personnel who excel in various professions within the Air Force. In general, the US military has a long history in collecting psycho- and biometrics, starting with Terman's testing of 1.7 million recruits on novel IQ tests in the early 20th century (Telman, 1918; Yerkes, 1921); it is possible that the USAF also has already a lot of data. It would be a tremendous advantage to have retrospective studies rather than collecting new data and outcome afresh, waiting to have enough temporal span to see meaningful trends. With machine learning, past and present data provide a basis for models that predict the optimal placement of personnel within occupations, as well as the value in retaining personnel/staff, for re-enlistment. Likewise, these data may be analyzed to identify, and in some cases anticipate, trends as occupations evolve due to the introduction of new technologies.

State of the Art: The primary tool used in assigning personnel to occupations within the Air Force is a written test (i.e. Armed Services Vocational Aptitude Battery (ASVAB) exam).

Goal: Supplement and update existing placement through the incorporation of data analytic techniques to identify the characteristics of USAF personnel that predict success within a given occupation and allow prioritization of personnel for re-enlistment.[5]

[5] One caveat perhaps worthy of note: even before the era of AI, a lot of the systems and institutions that implemented quantitative analytics (healthcare, education, industry) have discovered some quirks whose long-term accumulation has proved damaging. For example, some important skills in healthcare that are not quantifiable are selected against because the metrics do not recognize their value. The major recommendations have been (1) mixed evaluation, quantitative and qualitative (Mertes, 2014; Hussein, 2015) or (2) meta-analytics to model the need for new outcome measures (Lazar, 2013) - which also requires human intervention. We assert, until that later time (not the 2030 horizon) when general AI are developed, AI will only be one toolset to complement a softer qualitative evaluation of human performance - or performance metrics. AI cannot by itself discover gaps in its reasoning methods and decide from itself it needs a new quantitative measure of outcome, for instance. So, it is likely that officers will continue to do judgments on people or on tools to judge people, with the support but not with the exclusivity of AI analytics. Placement and retention indeed, is a classic example of skill that AI might not autonomously handle.

Vignette: 2030's Cyber Warriors

Technically, Lizzeth began her career as an Air Force Cyber Forensics Officer when she was in 5th grade and joined an after-school Air Force sponsored club for kids. After school and on the weekends, kids would hang out, learn the ins and outs of computers, how to create their own AI's, and how to use machine learning to tackle big data problems.

The timing could not have been more perfect because her job categorization did not exist even just a year before she enlisted. Data mining algorithms had recognized a cluster of activities that prompted the Air Force Personnel Center to create a job for personnel with the knowledge and skills to excel at investigating cyber breaches. This job involved identifying an adversary and determining their motives, intent, capabilities, and what they knew and did not know about the Air Force networks, as well as who they might be working with and who was elicitly supplying them with unauthorized access and capabilities.

Her training post-enlistment had been insanely hard... much more challenging than anything she had seen since she assumed command of her element of AI bots. It was only in the past few years that the Air Force had replaced the personnel doing low-level cyber operations with AI bots. Training had placed her in a virtual cyber command station and presented scenarios where networks essential to ongoing real-world missions had been compromised by multiple adversaries using overlapping but different strategies and possessing overlapping but distinct understanding of the Air Force networks and defensive strategies. For Lizzeth, it was like being the main character in six different episodes of a television crime drama... all unfolding simultaneously. The stress was real. By using real-time monitoring of her stress levels, fatigue, and other physiological responses, the simulation repeatedly took her to the breaking point. Her training was as much about honing her investigative skills as it was about managing her stress levels and using biofeedback methods to call upon her own inherent psychophysiological resilience resources. On top of all of this, she had to learn the skills needed to handle over 100 semi-autonomous AI bots that did not always behave in the way she expected.

However, Lizzeth had prepared for this job since she was in elementary school and she knew that when her assignment was nearing its end, the Air Force would offer her pre-enlistment package that was competitive with anything she would receive in the private sector.

d. Multiple Entry Points for Those with Specialized Skills.

Description: At present, individuals with specialized skills, such as cybersecurity, can make substantially more money and have a guaranteed job in their field in the private sector (Cyber Posture of the Services, Senate Subcommittee on Cybersecurity, March 13, 2018). Meanwhile, the USAF is unable to recruit many of these individuals and instead may ultimately hire them as contractors - at substantially higher pay and without direct oversight. It seems likely that integrating a new career pathway (i.e., alternative means of recruitment) could be essential to maintaining a dominant USAF workforce.

State of the Art: The USAF currently allows medical, law, and ministry officers to enter through a direct commission process (USAF, n.d.). However, to our knowledge, this is the only alternative entry to active duty other than joining in an enlisted or officer position without a pre-specified role.

Goals: As the USAF approaches 2030 there will be a need to re-examine how individuals are recruited and what roles they are promised in order to attract individuals with sufficient skill sets. For example, a highly skilled individual in the field of cybersecurity may be unlikely to join the USAF through traditional officer recruitment methods: there is currently no guarantee that they will end up the field they are skilled in, they have no control over where they will be stationed, and the pay is usually considerably lower than what they would receive in the private sector. However, if the USAF were to examine a direct commission process for highly skilled rolls for the officer ranks, it may alleviate this issue. Similarly, the enlisted ranks may benefit from either an alternative technical rank system or a differential pay system for those with special technical skills in order to recruit and retain those with specialized skills.

II. TRAINING THE AIR FORCE PERSONNEL OF 2030

Figure 14: Intelligence analysts allocated to the 11th Special Operations Intelligence Squadron attend a data-tagging training Aug. 24, 2017, at Hurlburt Field, Fla. Data-tagging is an AI-led effort to support with information gathering (photo credit: Air Force Special Operations Command Public Affairs; Sept 13, 2017).

As the USAF moves towards 2030, it will be necessary to envision new training processes to accommodate the adoption of new technologies. With AI becoming more powerful, scalable, and readily available, it may change the very nature of USAF training, particularly for technical or highly skilled jobs that can be taught through simulation. An important AI application is that of "Personal recommender systems," AI that suggests skill acquisitions to people under its monitoring (Drachsler et al. 2008; Fischer et al. 2007; Manouselis et al. 2011). Furthermore, augmenting human abilities, both physical and cognitive, may require the development of novel training methodologies to properly equip USAF personnel with the necessary skills to be successful in their role. In this section, we discuss key considerations in relation to training the USAF of 2030.

a. Technology-Enhanced Training for Air Force personnel.

Taskwork Training:

Description: Training in the USAF takes multiple forms. For this report, we are concerned with five types of technology-enhanced training that can benefit from the integration of AI: computer-based training, augmented reality, virtual reality, Live-Virtual-Constructive simulations, and technology-enabled psychomotor training.

Computer-based training: Computer-based training (CBT) has become ubiquitous throughout many forms of informal, formal, and professional education, including the defense sector (Sheets et. al., 2018). This term will be used as an all-encompassing term to include systems such as self-paced online courses and intelligent tutoring systems.

Augmented Reality: Augmented reality (AR) environments are those in which the real world is still visible to the trainee; however, computer-generated images are inserted into the actual environment (Berlier et. al., 2018).

Virtual Reality: Virtual reality (VR) environments are those in which the trainee is completely immersed in a technology-based learning environment. For example, a computer-generated simulated world that the trainee experiences through a head-mounted display (Haring et. al., 2018).

Live-Virtual-Constructive (LVC) simulations: LVC training systems provide training experiences that combine personnel in operational platforms, personnel in simulation-based training systems, and computer-generated entities to conduct coordinated training missions (Hodson & Hill, 2014; Hodson, 2017; Jung, 2018)).

***Technology-enabled psychomotor training*:** This form of training is broad and includes systems that use exoskeletons to help guide arms or hands to improve the learning of necessary dexterity and movements, combined with task-related declarative knowledge (Agarwal, 2017).

State of the art: Computer-based Training, Augmented Reality, Virtual Reality, and LVC-based instruction currently exist and have been deployed at various scales by the Department of Defense. While we have instructional design models based on human cognition to guide this work within multimedia CBT environments (e.g., Cognitive Theory of Multimedia Learning, Mayer, 2014), less guidance exists for the theory-driven design of AR, VR, or Live-Virtual-Constructive (LVC) simulations.

A current issue with AR/VR technologies is that they often create simulation sickness, a type of motion sickness, in the user (Ihemedu-Steinke et al., 2017). Also, often the AI powering these systems (at least in the commercial sector) are focused on creating appropriately scaffolded AI at a ‘one-size-fits-all’ approach rather than truly individualized instruction (Greer & McCalla, 2013; Holt et al.,1994). This is particularly true in multi-actor environments where more than one human is interacting with the environment at any point in time (DeCostanza et. al., 2018). While researchers have created effective Intelligent Tutoring Systems (ITS) for one learning domain for single users, we do not currently have many, if any, examples of ITS that are interactive between users (e.g., one user’s decision impacts another user’s learning pathway in a team-based environment), especially if physiological data is involved.

Goal: There are a plethora of opportunities to leverage AI and big data to scale and improve simulation-based training systems. For example, envision a simulation which contains 150-200 simultaneous participants, and the AI can appropriately tailor each individual's experience as they progress through the simulation with real-time feedback from how their interactions with the system influence the other users. There also is a need to reduce or remove the incidence of simulation sickness in AR/VR environments.[6] Finally, technology-enabled psychomotor training could leverage AI to teach a variety of different skills to those in skilled trades and scaffold each Airman's learning appropriately.

b. Teamwork Training.

Description: Teamwork and taskwork training improve mission outcomes through team performance (McEwan et al., 2017; Salas et al., 2017, DeCostanza et al.,2018), with teamwork training designed to enhance the functioning of a team and taskwork training focused on strengthening the technical aspects of executing work. Studies assert that affective response influences cognition (Leutner, 2014; Plass et al., 2014; Plass & Kaplan, 2016), but a well-defined theory integrating cognition and affect has not been presented, nor is it clear which affective constructs may be the most important to foster learning outcomes, particularly in warfighting contexts.

Various mechanisms may be employed to assure trainees are in an optimal psychological and physiological state and have an affective perspective (i.e., beliefs and attitudes) that will maximize learning outcomes and operational performance. Similarly, training may incorporate the skills needed to assess the affective state of others and take measures to manage the impact on individual and team performance. These interventions equip trainees with the skills needed to cope when exposed to real-world stressful operational experiences effectively.

A related line of research exists around affective computing (Picard, 2003; Cambria 2016), which entails building an understanding of how a computer can sense and react to learners' affective states in real time, and then present appropriate instruction based on the affect detected.

State of the art: Although there is burgeoning literature of technology-based team taskwork training, much less progress had been made across domains (e.g., industry, healthcare, military). Few studies of teamwork training intervention have incorporated technological innovations for teamwork training and even fewer used any AI (McEwan et al., 2017; Salas et al., 2017). Some studies have reported neuro-based analytics (Likens et al., 2014; Dodel et al.,2011; Dodel et al., 2013; Cook, 2015).

[6] High speed trains have studied this issue of the dissociation between proprioception and vision and offered solutions (Persson et al.,2009; Zhou & Goodall, 2014).
This body of knowledge might inform us about the issue of AR/VR.

Goal(s): Interventions for teamwork training are most effective when they target multiple teamwork dimensions and involve experiential components such as simulation scenarios (McEwan et al., 2017), making the area ripe for approaches such as VR, AR, or LVC simulations. To capture the complexity of teamwork across mission tasks, multi-model methods that capture data and deliver simulation experiences are needed. Advances in teamwork training that use approaches such as AR systems that incorporate biometric and behavioral (e.g., speech, gestures, facial expressions) data can be used to provide both multi-sensory simulation experiences as well as real-time adaptations of the training. Multi-model inputs to an AI system related to responses of individual to tasks as well as individual responses to other team members (actions/emotions) can serve to tailor the training in real-time. Such adaptive systems have the potential to maximize the level of the training challenge for each Airman as well as the team and may produce optimized teamwork and team performance outcomes.

In addition:

- Little progress has been made in the application of adaptive 3D virtual learning environments for collaboration, suggesting that new methods are needed to address the complexity of multiple user's needs (Scott et al., 2017).
- New models of collaboration and collaborative learning, including assessment of interactions, are needed to account for technological advances in brain-computer interfaces, brain-computer-brain interfaces, and brain-brain communication (Kerous & Liarokapis, 2017).
- New challenges in teamwork training will arise in response to new types of team members/diversity. The ability to provide individually tailored adaptations are particularly relevant as teams increasingly include enhanced/cyborg members. Adaptations can help account for unprecedented differences in capabilities across individuals and support teams to learn how to leverage relative strengths and weaknesses. The often dynamic fluid/permeable teams will place greater emphasis on competencies associated with the assessment of team members skills and flexibility to work with the unique team profiles related to expanding variability in the types of enhancements of the next generation of Air Force personnel.

c. Cognition and Affect-based Training.

Description: At the individual and team levels, training outcomes are impacted by the psychological conditions and corresponding physiological state and the beliefs and attitudes of trainees. Likewise, the chronic and acute well-being of individuals and groups is dependent upon their ability to effectively cope with stressful experiences, both during training and real-world operations. Researchers have long sought how to present instruction to benefit learning, however, many current instructional design theories are focused on purely cognitive factors (Mayer, 2009, 2014; Sweller, 2010; Sweller et al., 2011). Recently there has been increased interest in how affect influences cognition.

State of the Art: There are cognitive theories broadly applied to the domain of multimedia learning and learning in general (Mayer, 2009, 2014; Sweller, 2010; Sweller et al., 2011). Work to extend these theories to include affective factors has been proposed, but often presents comparably vague theoretical models (Moreno & Mayer, 2007; Plass & Kaplan, 2016).

Recent work in the area of affective computing has aimed to expand understanding of how computers can sense learners affective states (through means such as facial recognition, text, physiological data, or other measures (D'Mello et al., 2018; Poria et al., 2017).

Various biometric sensing devices have been shown capable of assessing the affective state of an individual, as well as other parameters such as fatigue and acute levels of stress (Faundez-Zanuy et al., 2013; Gupta et al., 2012). Immersive experiences based on placing trainees in either physical or virtual environments have been incorporated into training, although it is uncertain the extent to which these experiences produce a psychological/physiological response comparable to the actual experiences being simulated (Andreatta et al., 2010; DeMaria et al., 2010; Fraser et al., 2012). The ability to recognize the affective state of others is recognized as a metacognitive skill that can be trained (Kuhn, 2000; Sodian, 2008). Research has been conducted to understand the acute and chronic psychological and physiological responses of personnel to stressful environments and intervene through various mechanisms to minimize the associated adverse effects (Brewin et al., 2000).

Goal: Models are developed that describe individual differences in psychological and physiological responses to a wide range of operational experiences, and the efficacy of interventions on the acute and chronic well-being of personnel. These models provide a basis for developing technologies that monitor psychological and physiological responses to stressful experiences as a real-time component of training, which could occur through traditional sensor technologies (Kapoor & Picard,2005; Arroyo et al.,2009), smart textiles (Valenza et al.,2010; Lee & Chung, 2009; Axisa et al.,2003), or non-invasive sensors. Based on associated data collection, AI-based interventions may be implemented on an individual and organizational level to improve individual and team performance in stressful situations, and maximize well-being, as well as to adapt simulation-based training so it is tailored to the training needs of individuals and teams (e.g., managed stress exposure). Moreover, it will be important to give robots affective capabilities also (such as emotions). This will make them more effective and survivable (Long, 2015).

Basic science research is also needed to extend our understanding of how cognition is mediated or moderated by affective processes, which then holds implications for how all instruction, including AI-based instruction, should be designed. This work is needed from the basic scope of CBT through LVC scenarios, and it is possible that essential mediators or moderators may differ depending on the learning environment.

There is room to create more accurate, descriptive, and theory-driven models of how affective computing systems should react to learners' emotional states. This includes basic science on the improvement of the algorithms detecting and interpreting affect as well as building our understanding of how and when a computer should customize the instruction based on the affective states identified.

***Vignette:* Airman Kris's Unit Deploys to the Virtual Battlefield**

Airman Kris is an Air Battle Manager in training. Kris has gone through the traditional classroom-based instruction and is now preparing for their first deployment. As part of a Live-Virtual-Constructive simulation, Airman Kris is connected to a Virtual Reality environment where she interacts with the same equipment she would in theatre. Meanwhile, pilots are connected to the simulations through their own immersive flight simulators, and their officers are stationed within a mixed reality command and control center that show virtual representations of where their Airman are on the battlefield. There are also radiomen within the command and control center who can communicate with all appropriate parties, and everyone involved is wearing smart fabrics that record a variety of physiological signals (e.g., heart rate and galvanic skin response) which are fed into the systems AI.

As the simulation proceeds, data is collected about every participant's actions, and an individualized AI system responds in kind to every reaction they take to help scaffold their learning experience. As the individual gains experience, their AI will make the simulation progressively more challenging by presenting a variety of new challenges. For example, on the Day 3 of simulation training, Airman Kris has made satisfactory progress with her communication skills, so the AI decides to simulate an enemy jamming her primary communication devices, forcing Kris to run through her jamming protocols. Meanwhile, on Day 5 two of the three pilots have not made satisfactory progress, so they are provided individualized guidance on how to improve their evasive maneuvers, and simultaneously those in the command and control center are exposed to a simulated direct hit by an enemy mortar that injured one radio operator and the executive officer. Since everyone is wearing smart fabric uniforms, when the medics respond they are presented with the symptoms of a sucking chest wound on the radioman and a fractured tibia for the Executive Officer. The medic working on the sucking chest wound has shown excellent progress in treating this injury on other simulated patients, so the AI training system also present a cardiac failure. Responding to this situation, Airman Kris calls in a medevac to evacuate the wounded.

d. *Training to Become a Technologically-augmented Airman.*

Description: It is possible that in 2030 the USAF will be recruiting Air Force personnel specifically for roles as potential cyborgs. We posit that cyborgs will be either physically-enhanced, where they are provided with some physical augmentation or ability, or cognitively-enhanced,[7] where they are provided with some cognition-enhancing augmentation or ability. Appropriate training methodologies for these individuals will need to be developed.

State of the Art: Evidence-based training paradigms currently used for physical therapy and rehabilitation provide relevant examples of training which could be used as starting points in the development of training program related to physically-enhanced cyborgs. Amputees, for example, may receive such training when first provided with a prosthetic limb. Similarly, for cyborgs with augmented cognition or enhanced sensory capabilities, training would be needed for Air Force personnel to operate effectively using night vision or thermal imaging technologies.

Goal: As new forms of cyborgs emerge, and humans are physically, and cognitively-enhanced, new training methodologies will need to be developed to teach augmented humans how to use their new abilities.

e. *Neurotechnologies to Enhance Learning.*

Description: Presently, training a member of a civilian or military organization in relevant skills is a highly resource-intensive process both in terms of time and expense (Shanley, 1997; Horowitz, 2017). Further, naturalistic learning requires frequent repetition and practice to solidify acquired skills. This, in turn, necessitates extended training periods and periodic instructional "refreshers," which represent an infrastructure and logistic challenge. Other aspects of modern skill contexts (such as organizational turnover and rapidly changing skill requirements in evolving technological and social norms context) further complicate training and retraining strategies across all warfighting domains of the USAF. Finally, treatment of pathologies relevant to involuntary memory retention (e.g., PTSD) currently is limited to behavioral therapy interventions that require costly and prolonged treatment at specialist facilities. Non-invasive electrical neurostimulation of the brain for skill acquisition, increasing learning, and memory enhancement (Pollok et al. 2015; Antal et al. 2004; Zaehle et al. 2011) is a transformative technology that could drastically change training programs of the USAF (and beyond) for the better, reducing overall costs of personnel recruitment and training, while maintaining increased levels of competence throughout the organizational population.

State of the art: Recent advances in the basic science and application of non-invasive neurostimulation technology include trans-cranial magnetic stimulation (tCMS) and trans-cranial current stimulation (tCCS) and have enabled augmentative neural interventions that extend the

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[7] Pharmacologically supported learning would inform how to achieve the enhancement (subject to risk and ethics) (Chatterjee, 2006; Hussain & Mehta, 2011, Greely et al., 2008).

human ability to rapidly obtain new knowledge and retain newly acquired knowledge beyond what is possible with naturalistic learning and training.

While all the relevant applications have not been identified to date, robust, replicable research have demonstrated enhancement of performance in complex, real-world tasks using novel forms of neuromodulation based on a deeper understanding of underlying brain principles and mechanisms. Recent advances have shown how 1) acquisition/retention of *specific* novel information in naturalistic can be increased; and 2) generalized acquisition/execution of skills and transfer learning are improved in terms of consistency and precision, using targeted closed-loop waking and sleep interventions.

Goal: By 2030, the USAF will have completed the development of non-traditional modalities for non-invasively sensing and modulating neural circuits non-invasively with more precise spatial resolution and faster temporal resolutions. These newly developed tools and devices coupled with machine learning, sensor fusion, control theory, and brain decoding and encoding, will enable and accelerate the deployment of revolutionary co-adaptive non-invasive systems for application-agnostic enhancing human performance.

III. HEALTH, PERFORMANCE, AND WELLBEING

A healthy workforce is a more effective, less expensive workforce (Fabius et al., 2013). As the USAF moves towards 2030, it will be essential to monitor and improve the health and wellbeing of AF personnel. AI, biohacking, and a host of future technologies may change the face of what we know and how we treat health and wellbeing. In this section, we discuss key considerations creating a better understanding of what (and how) various factors influence Air Force personnel performance and readiness.

a. Future Humans.

Description: The physiological makeup of the Corps of the future will range widely. At the one end of the spectrum and perhaps closest to present-day Air Force personnel are people whose medical limitations are remedied with implants (such as insulin pumps or spinal stimulators); these implants may allow them to serve. Injuries or new medical conditions that presently lead to a medical discharge may be mitigated so the Air Force personnel may continue to serve.

Near the middle of the spectrum, phenotype-modified[8] personnel may provide the Corps with a physiological or cognitive advantage. Not all phenotypical modifications necessarily involve gene-editing. For example, a biomic (gut microbiome) transplant of new, modified bacteria may confer resilience or allow for a specialized, performance-enhancing diet. Epigenetic control of gene expression is now reasonably well characterized in a variety of human and non-human biological systems. Therefore, it may be possible to enhance the visual perception of human operators by modifying the expression of photoreceptor genes such that both infrared and ultraviolet light can complement the normal human visual spectrum. Such enhanced visual perception would allow pilots to see through clouds without the use of radar. Finally, bone marrow transplant of gene-edited bone marrow stem cells could provide a mechanism to provide advantages such as improved oxygen carrying capacity or improved immunity.

[8] Phenotype-modified mean people who are modified/enhanced but these traits are not passed through the germ line to offspring

***Vignette:* Ross Spacewalks to Repair Damaged Craft.**

Ross had always wanted to serve in the USAF, but at the age of eighteen, he was diagnosed with Acute Myeloid Leukemia. When the treatment option turned to bone marrow transplantation, Ross assumed his condition meant he would no longer be fit to serve. However, when he shared his concerns with his doctor he learned of a special program through the USAF that would allow him to potentially serve in space missions if he received bone marrow stem cells that had been genetically modified to produce erythrocytes with improved oxygen carrying capacity. After discussing the risks and potential benefits with his doctor, and a quick consultation with a USAF recruiter and medical officer, he decided to receive the genetically modified bone marrow. Following successful transplantation, which cured cancer, he enlisted in the USAF and successfully trained for space missions. His improved endurance and cognitive functioning, thanks to the genetically modified bone marrow stem cells, help his team complete the needed repairs.

At the far end of the spectrum, the advent of commoditized gene-editing technologies has made it possible to 'word process' the human genome with high efficiency and specificity. A germ-line modified human (who would, therefore, carry a modified version of a gene in all the cells of the body and may pass on that altered gene), might be useful for the permanent modification of cancer-causing genes. For example, in face of the dangers of space radiation, an improved version of the UVRAG gene may provide improved resistance to UV radiation; alteration of CDKN2A may also confer a decreased risk of melanoma.

State of the art: Limited to implants (such as insulin pumps or spinal stimulators).

Goal: It is likely that genetic modifications offering cognitive enhancements will emerge as an option for Air Force personnel. The classification of human modifications along the spectrum (illustrated above) will be blurred to the point they may not be relevant in the future, but for now, allow us to consider the alterations possible with future personnel. Biologically-based improvements to human cognition may occur from breakthroughs along any point in the spectrum.

b. Implications of the Extreme Environments Associated with USAF Mission Areas on Physiology and Psychology.

Description: Extreme environments will have implications for the USAF mission areas. NASA defines these five environmental challenges for astronauts: gravity fields, isolation/confinement, hostile/closed environments, space radiation, and distance from earth.

State of the art & Goal(s): There is ongoing research addressing the effects of these environments on health. However, because some of the conditions will have latent, long-term health effects, we anticipate this research will continue through the 2030 timeframe. Besides, as noted in the section regarding the increased complexity of the medical conditions of active service personnel, new machine learning or other analytical techniques will be needed to make sense of complex, multifactorial datasets (Su et al., 2017).

Also, research will be needed to identify traits that convey resistance to stressors or enhance survivability in these austere environments. Some of these traits may be cognitive/psychological, present in unaltered populations, and simply require further personnel selection research (and related changes to Air Force personnel recruitment practices); other traits may only manifest because of genetic predisposition. There may be a convergence as individuals are groomed (already possess intrinsic advantages or skills), trained (to further improve skills), or otherwise medically prepared (see example in above section about transient enhancements) for specialized missions or roles.

c. Cryogenic Hibernation for Space Travel

Description: Cryogenic Hibernation will play a role in long distance space travel. The outside of the capsule environment of deep space potentially provides an energy efficient way to maintain a hypothermic or cryogenic state.

State of the art: Currently, clinically-induced hypothermia—reducing core body temperature to 33 °C (normal is 38.5 °C) for up to 72 hours—is in use for its neuroprotective effects (Badjatia, 2017).[9] Beyond the utility for long voyages, could Cryogenic Hibernation or temporary Hypothermia provide resistance or enhanced survival through a region of intense radiation or be a treatment option for infection or disease?

Goal: Success will depend on a hypervigilant AI for maintenance of physiological homeostasis and as well as to determine the right time to awaken the traveler.

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[9] There is also the important area of vitrification developed for assisted reproduction: it has refined techniques for long term storage of human embryos, as well as protocols for the return of those human organisms at normal temperatures. I do not foresee a development of adult cryogenic protocols that would not heavily borrow from the large body of knowledge therein accumulated. Besides, if robotics was making large progress for childcare, then it would become an option on the table to send embryos, and not developed humans, in long term missions - minding the ease of storage and thawing, but with ethical reservations.
Choi, D. H., Chung, H. M., Lim, J. M., Ko, J. J., Yoon, T. K., & Cha, K. Y. (2000). Pregnancy and delivery of healthy infants developed from vitrified blastocysts in an IVF-ET program. Fertility and Sterility, 74(4), 838-839.

Rall, W. F., & Fahy, G. M. (1985). Ice-free cryopreservation of mouse embryos at− 196 C by vitrification. Nature, 313(6003), 573.

d. Medical and Mental Health Issues in Service

Description: Increased youth sports-related injuries, youth obesity, vaping, prior history of opioid abuse, and self-biohacking will present new challenges as recruits entering service will have more complicated medical histories or conditions. This includes both physical and mental health considerations. One emerging mental disease is chronic traumatic encephalopathy. Since this disease affects cognition and mental health, it could affect future Air Force personnel. In addition, since implantation for enhancement is a future possibility, implants for states that currently may disqualify for service, such as diabetes, may be allowed.

State of the art: AI is now used to suggest a diagnosis or suggest a treatment, but it is not integrated to do the longitudinal decision-making that a human physician does.

Goal(s): Multimodal diagnosis[10] enabled by AI will better define individual effects of illness and injury on cognition and psychological health over different timescales (acute, short-term, long-term). Current concepts and methods of diagnosis and treatment for concussion and PTSD (for example) continue to evolve, for example, and will soon consider petabyte scale longitudinal clinical data. The use of AI to help diagnose, monitor and treat conditions (especially emerging neurological conditions) that negatively impact cognition, should expand. In addition, the USAF might consider recruiting personnel that possesses highly-specialized skills and talent critical to AF mission success (for example, Cyber) despite the presence of currently-disqualifying medical conditions or implants.

In addition:

Beyond better integration and standardization of Electronic Health Records (EHR) between the DoD and VA systems, there will be a need for better integration with civilian EHRs, particularly since USAF personnel may leave and then return to service multiple times during their careers.

The increase in volume and complexity of medical data will require new machine learning, modeling, visualization, and other predictive analytic techniques to aid DoD physicians through smart decision support tools. While similar algorithms or platforms will be developed commercially, they would need to be adapted given the specialized personnel and mission requirements of the USAF, which could include prolonged deployment and extreme environments. It should be kept in mind that the data centers generating, and processing data would require huge investment in terms of energy cost and security (Ajmera et al., 2018; Cutler et al.,2017; Burger et al.,2009; Khan & Zomaya, 2015).

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[10] Multi-modal diagnosis entails incorporating many different data points into the decision as well as evaluation data over time. Considering personalized genetics in a diagnosis would be characterized as multi-modal diagnosis.

***Vignette:* Drone Pilot Paul's Unit Fights Back Against Post-Traumatic Stress Disorder**

Paul is a drone pilot who regularly is posted on missions in which he is ordered to eliminate enemy combatants. Due to the high incidence of PTSD among drone pilots in his role, Paul's regular mission debriefing takes place with a virtual system. Paul answers a variety of questions and the system AI analyzes whether or not he is showing indicators of PTSD (and the particular stage of PSTD) in order to make recommendations that he seeks treatment, while also notifying his commanding officer and unit psychiatrist when necessary. There is less stigma attached to seeking help for mental health issues as interacting with the system is part of the required debriefing sessions for everyone in the unit. Since the unit psychiatrist is provided the data, there is no reliance on Paul to seek treatment, as the psychiatrist can approach him directly. Post-debriefing, Paul gets an individualized treatment that is based on "resilience" factors he possesses.

IV. SUSTAINING THE WORKFORCE AND QUALITY OF LIFE

A quality workforce should be a critical priority for the USAF of 2030. Maintaining such a workforce consists of several factors, but Air Force personnel career development and quality of life are essential concerns. In this section, we discuss these issues in relation to AI and augmented cognition.

a. Harnessing Data to Develop Individualized Career Development Models:

Description: During training and operations, data may be collected as Air Force personnel interact with computing systems, utilize various means of communications and are the subject of biometric and other physiological measures. At an individual level, this data may be used to develop models that reflect the knowledge, experience, and performance of personnel, while tracking individuals as their performance improves (or degrades) over time and as they respond to external events (e.g., high tempo operations, emergency responses) At an organizational level, these models may be aggregated to identify trends, and impending strengths and weaknesses, as well as to map the knowledge and experience of the organization.

State of the Art: Today, research with intelligent tutoring systems has been applied to create computational models of expert performers, assess student knowledge and proficiency and effectively intervene to automate portions of instruction or achieve improved outcomes (Dixon et al., 2009; Stevens-Adams et al., 2010). Multiple meta-analyses have shown that intelligent tutoring systems can be effective for learning (Hu & Cooper, 2014; Ma et al., 2014). Data analytics (e.g., educational data mining, learning analytics) has been utilized to improve system performance, personalize systems (e.g., user interfaces) and provide targeted recommendations and advertisement (Evans, 2009; Siemens, 2013; Webb, Pazzani, & Billsus, 2001). Similarly, user modeling has been employed as a means to structure human-machine transactions to maximize individual effectiveness and tailor systems to the idiosyncratic needs of individual users (Schiaffino & Amandi, 2004). Through the Life Logging movement, many groups and individuals are regularly experimenting and sharing their experiences as they collect and utilize data collected during day-to-day, real-world experiences to gain greater personal insights and improve performance and well-being (Potts, 2016).

Goal: Technologies are implemented that provide acceptable levels of privacy and personal data ownership that enable the Air Force to collect data from individuals and organizations to maximize effectiveness and minimize the cost of training. These capabilities allow the Air Force to conduct detailed, real-time assessments of individual and organizational readiness with respect to performance proficiency, knowledge and experience and proactively intervene to address potential shortfalls.

b. Human-Cyborg Workforce Organizational Culture:

Description: The Air Force developed in response to the introduction of new machines – airplanes - into warfare. From its inception, the USAF workforce has relied on machines to carry out its mission, and that reliance has rapidly increased over time with advances in technologies. By 2030, USAF workforce will not only continue to increase its dependence on machines but will face novel issues such as preparing, supporting and managing a workforce increasingly comprised of individuals integrated with machines (e.g., cyborgs).

State of the art: [Cyborg] workforces are emerging through the development of enhanced prosthetics and use of technologies such as small chip implants (e.g., to open secured doors).

Goal: While [an enhanced} workforce offers strategic advantages; such a workforce introduces new challenges associated with potential shifts in values and organizational structure and culture. Acceptance and competition among augmented and non-augmented individuals may impact workforce functioning (e.g., team effectiveness). Enhanced performance capabilities among [enhanced] workforce may introduce new informal (e.g., social) or formal (e.g., military) ranks and impact career trajectories and promotion. Understanding the social and organizational implications of a diverse and integrated workforce(s) is critical to support the integration of a diverse workforce, including cyborgs and genetically engineered human beings.

C. Research Questions

Several critical issues emerged organically during group discussion. The team raised pertinent questions for further exploration. We club the questions in categories for convenience below.

Questions related to workforce composition:

- How do we determine high impact skills in 2030 across all three mission areas, and how can data analytics be employed to assist this process?
- What jobs will exist in the USAF of 2030 that do not exist now, and can data analytics be used to identify trends that are predictive of emerging jobs?
- How should recruitment and retention change in the USAF of 2030, and can data analytics be combined with economic models to prioritize personnel for retention and develop competitive compensation packages?
- What features, or skills associated with adoption of AI and Augmented Cognition technologies be needed for recruits of 2030?
- How do we develop interventions that create sustained enthusiasm and commitment to STEM-related fields that will be essential to the Air Force in 2030, and cultivate the workforce that will be needed, both with regard to Air Force personnel and organizations that support the Air Force? How do we recruit airman with complementary innate talents for dedicated teams?

Questions related to training of the Air Force personnel:

- What specific affective factors mediate or moderate cognition in distinct types of learning environments (CBT/AR/VR/LVC)?
- How should VR/AR/LVC environments be designed to best support learning? There is a need for theory-building research around virtual environment design.
- What advances need to be made in software (including AI) to support individualized instruction for many trainees simultaneously?
- What hardware advances need to be made to support individualized instruction for many trainees simultaneously?
- What advances can be made to reduce or eliminate simulation sickness when using AR/VR technologies?
- Development of non-invasive and minimally-invasive techniques for sensing stress, fatigue and other affective states that may affect learning?
- How do we train future cyborgs, both physically and psychologically?
- What are human vulnerabilities in relation AI-inspired attacks?
- What elements of teamwork (add examples of specific areas) are essential to drive effective AI teamwork training systems?
- How do we understand the appropriate hierarchy of authority/control/leadership of fully autonomous teams?
- What are the bases for decision making in such teams? How can the team adapt when the machine leader is disrupted (e.g., shot down)?
- When does a machine-machine team need to revert to humans for control?
- How do we prevent, minimize, or control for, human bias in our models?
- What will be the balance between bringing personnel that possess highly specialized skills and talent critical to AF mission success (for example, Cyber) who otherwise have medical conditions/implants that might be disqualifying?
- What is the relationship between biometric markers and teamwork processes (e.g., physiologic responses to productive vs destructive conflict)?
- What are the biometric response patterns among team (dyad/interaction)?

Questions on Health and Wellbeing:

- How do we identify psychological and physical readiness of incoming recruits?
- Which biomarkers can predict performance and resilience?
- Can we create an automated psychological profile system to predict cognitive vulnerabilities, affinities, strengths, and weaknesses?
- Do current or future AF roles or mission sets increase the risk of PTSD or CTE? Are there characteristics (genetic or cognitive) that decrease the risk for long-term cognitive impair of the Air Force personnel?
- Given the improvements to AI, can we develop a more interactive assessment paradigm that better characterizes the multiple facets of human cognition?
- Once better characterization of human cognition is available, can AI/machine learning be used to provide better optimization into job roles and improve team formation?

- Will USAF weigh the pros and cons of hiring personnel with highly specialized, mission-critical skills and talents (for example, Cyber) who may have otherwise disqualifying medical conditions/implants?

Questions related to sustaining the workforce and quality of life:

- How to effectively intervene based on real-time data to improve training outcomes?
- How to integrate behavioral performance data and physiological data to tailor training to individuals in real-time effectively?
- How will the introduction of [cyborgs] influence the value structure of the workforce?
- How will global competition/response to enhanced military workforce influence
- How does the introduction of biological/physical, cognitive (e.g., computing, processing, decision making), behavioral/emotional (e.g., empathy) enhancements influence social or military ranks/status among Air Force personnel?

5. CROSS-CUTS

a. Ethics

The question of how the AI Acceleration will affect ethical, legal and social issues across the USAF and larger society was repeatedly raised during the online and face-to-face components of this project in many contexts.

Right to Explanation:

One of many examples that will cross-cut the entire USAF mission space because of the AI Acceleration is the "Right to Explanation" (Wallace & Castro, 2018). The phrase is used for the process of explicating how an AI realized a conclusion that has human consequences (e.g. kill chain). The Right to Explanation is both a concern today (Goodman and Flaxman, 2016) and is likely to be the case in the future without significant advances in the computer science underlying AI.

As with any transformative technology, AI raises new ethical and legal questions, related to liability or potentially biased or instructed decision-making. The European Commission has announced a series of ethical guidelines for AI, mostly focused on commercial uses.

In a similar vein, the rapid employment of AI as a tool that transforms national security has raised further concerns. This is not only due to the use of AI for military and information superiority but also due to alarming weaponization prospects (UN Convention on Conventional Weapons Group 2018) and the need for ethical design (IEEE, 2016). Although it yet remains to be seen how "intelligence" is legally assessed in AI-driven systems (Karanasiou et al., 2017), clear principles for AI's accountability and intelligibility (Goodman et al., 2016, Selbst et al., 2017, Wachter et al., 2017, Doshi Velez et al., 2017) are crucial for their employment in military operations. To pave the way for fully operational AI-driven systems, careful consideration must also be given to their socio-legal context, addressing the levels of accountability for military operations relying on automated systems as well as their impact on international security and their potential to shape new norms.

b. Strategic Surprise:

Strategic surprise was another issue that was raised in many contexts of the intellectual discussions leading to the present report. Most often, this challenge to the USAF mission was posited in the form of advances in the AI Acceleration on the part of potential adversaries. An example of such strategic surprise would be the development of a General AI by China in advance of US success in that area, potentially out of the blue.

c. Logistics

A report from National Research Council (2014) entitled “Force Multiplying Technologies for Logistics Support to Military Operations” suggests that logistics studies and analyses increasingly struggle to support fact-based decision-making. AI might present some opportunity to remedy this symptom of complex organizational structures. AI seems to have been a key player in the recent competitive success of key companies including DHL (shipping), Amazon (shipping), KLM (chatbots to answer simple customer questions, autonomous booking system), GE (predictive analytics on production requirements for commercial aircraft engines), John Deere (manufacturing plant maintenance) and Alibaba (retail). At the cost of large initial investment, assorted with efforts to break data silos and hire data scientists (Cahmi, 2018), AI involvement in logistics has led, at least in those large companies, to a substantial reduction in shipping time and operational costs and increase in performance. In the context of a well-integrated, data-rich USAF, AI could support systems for logistic operations, including supply, distribution, maintenance, mission planning, traffic, and services. Supply chain management (SCM) could offer system-wide recommendations for improvement in efficiency. Supply analytics and forecasting (Jeble et al., 2017) could make the supply chain smart, with self-learning, so that it anticipates needs and increases readiness. AI-supported inventory management could enhance tracking, sorting and transporting of the parts that USAF need to maintain efficient operation throughout (DHL/IBM, 2018). With the development of machine autonomy, USAF will benefit from self-managing components and agents that imposes less burden on the workforce while increasing performance and readiness. An example is the commercial aircraft communications addressing and reporting system (Ungerleider, 2014). Finally, in support of the USAF workforce, AI could enable expert-assist: the retrieval of information on organizational knowledge, objects and persons, with Natural Language Processing and Artificial Image Recognition/Segmentation. An expert system, for instance, could identify meaningful contact personnel for an operational task (especially valuable to counter personnel turnover and the loss of institutional knowledge) and help access to knowledge and specification at a much faster rate than conventional human searches (DHL/IBM, 2018).

6. Conclusion and Recommendations

“Anything that could give rise to smarter-than-human intelligence—in the form of Artificial Intelligence, brain-computer interfaces, or neuroscience-based human intelligence enhancement - wins hands down beyond contest as doing the most to change the world. Nothing else is even in the same league.” —Eliezer Yudkowsky

Just as the development of the atomic bomb fundamentally changed the face of geopolitical competition, so too will the AI Acceleration. As a result, the mission of the USAF is likely to be profoundly affected.

The underlying physics behind nuclear weapons began to be understood at the turn of the 20th century (Lanouette, 2013) (reference), a full 45 years before the first weapon was detonated in Alamogordo, New Mexico. So too, the AI Acceleration began to manifest at the turn of the 21st century, and we await its culmination, although we can see the outlines of how it will manifest. The present report represents an early vision of how the AI Acceleration will play out in the context of the USAF mission by 2030.

The main conclusion of this report is embedded in the term used to describe what is happening in the field: the AI Acceleration. Acceleration implies non-linear change, and it is clear from the literature and the discussions that led to this report that this term describes the rapid developments and deployments of technologies across the spectrum that have applicability to the USAF. As with any phenomenon that shows such dynamics, forecasting is challenging. Nevertheless, the on-line and face-to-face discussions among the participants in this project reached consensus in three domains: machines, human-machine, and humans (these were summarized in the Executive Summary).

Besides, the discussions identified several cross-cutting issues. These include ethics, strategic surprise, and logistics. These were called out as cross-cuts not only because they had significance across this report’s logical divisions (machine, human-machine, human), but also because they were clearly cross-cuts over the mission domains of the USAF.

Finally, the following recommendations are made to the USAF to aid in its invention of the USAF of 2030:

- The USAF should coordinate its R&D investments in the AI Acceleration with other federal science agencies such as the NSF besides other parts of the DOD and the IC.
- The USAF should scan R&D investments globally to gain insights into foreign government plans & capabilities that may represent warfighting challenges of the future.
- The USAF should organize an AI Acceleration Advisory Committee of top flight researchers from academia and industry to provide USAF leadership information and advice as the various disciplines underlying the science continue to advance.
- The USAF should scaffold solutions by building platform technologies, data architecture, and integration capabilities that serve to underpin AI applications.
- USAF should create the position of executive data architect to oversee the integration of AI, collection and securitization of centralized information resources from equipment to logistic and human assets.
- The USAF should increase its funding of basic research in Artificial Intelligence and Artificial General Intelligence.

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8. Appendices

a. Community Membership (Hub members)

Alphabetized list by last name (includes both virtual and f-2-f participants)

James Aimone, Ramya Akula, Suzie Allard, Andreas Andreou, Bob Angell, Pierre Baldi, Maxim Bazhenov, Monique Beaudoin, Jonathan Beever, Anamaria Berea, Chris Berka, Ethan Bernstein, pierre berthet, Kate Bezrukova, Ali Borji, Christina Bouwens, Casey Canfield, Matthew Canham, Mason Cash, Jeff Clune, Nancy Cooke, Kevin Crowston, Ron Daniel, Son Dao, Virginia de Sa, Timothy Draelos, Maria-Jose Escobar, Jean-Marc Fellous, Stephen Fiore, Susan Fitzpatrick, Chris Forsythe, Jared Freeman, Sam Gannon, Sicun Gao, Luciana Garbayo, Ivan Garibay, Josette Gevers, C Lee Giles, Richard Granger, Jonathan Gratch, Stephen Grossberg, Kara Hall, David J. Hamilton, David Hamilton, Ryan Harne, Kyle Harrington, Ilana Heintz, Maartje Hidalgo, Todd Hylton, Kenneth Ingraham, Patricia Jones, Nadine Kabbani, Argyro Karanasiou, Ana Kasirer-Friede, Muhammad Salar Khan, Joseph Kider, Asimina Kiourti, Stuart Koehl, Jeff Krichmar, Frank Krueger, Amy Kruse, Keri Kukral, Kiran Kumar, Merle Lau, Falk Lieder, Lyle Long, Jessica Lundberg, Deborah Mantello, Barry Mauer, David METCALF, Shalini Misra, Eric Mjolsness, Patricia Bockelman Morrow, Prasanna Kumar Muthukumar, Ben Nguyen, Katy Odette, James Olds, Andrew Olney, Jacob Packer, Eleonore Pauwels, Giovanni Pezzulo, Dimitris Pinotsis, Margaert Polski, Alexandra Psarrou, Anna Rafferty, Elaine Raybourn, Emmett Redd, Anthony Ries, Saul Robinson, Tajana Rosing, Fred Rothganger, Ryan Hill, Paul Sajda, Brian Scassellati, Daniel Schoonover, Noah Schroeder, Ruggero Scorcioni, Elaine Sedenberg, William Severa, Michael Sinclair, Jerome Soller, Amber Story, Andrew Stricker, Gita Sukthankar, Grace Teo, Emmanuelle Tognoli, Donni Toth, Barbara Truman, Davide Valeriani, Pips Veazey, Melinda Villagran, Caroline Wagner, Yingxu Wang, David Wojick, Anita Woolley, Peggy Wu, Bei Yan, Huiru (Evangeline) Yang, Valarie Yerdon, Michael Yip, Kate Ziden

b. Workshop Agenda

Title: AI & Augmented Cognition in the USAF of 2030
Agenda Overview

The workshops included highly interactive hands-on activities whose exact proceedings emerged rather than transpired. The event had a starting point, a clear goal, and a few key milestones that the team hit along the way. The facilitation team (of Knowinnovation) was responsive and flexible in designing each day to the needs of the group and the goals of the event. Below is a brief sketch of the agenda that the group followed.

<table>
<tr><th>Day 1</th><th>Day 2</th><th>Day 3</th><th>Day 4</th><th>Day 5</th></tr>
<tr><td colspan="5">A hot breakfast buffet is available at the Hilton Arlington. The hotel is 1/2 mile (10 minute walk) from GMU. Car service is available on request in the Hilton lobby or by pre-arrangement back to the Hilton post-meeting. Our sessions will start at 9am each morning.</td></tr>
<tr><td>Welcome, Introductions and Call to Action</td><td rowspan="2">+10 Projects AIR & SPACE</td><td>+10 Projects LAND & SEA</td><td rowspan="2">ANNOTATING THE OUTLINE Part 2</td><td>Quick morning presentations & feedback</td></tr>
<tr><td>Into the Future</td><td>VETTING THE REPORT OUTLINE</td><td>Group writing Time</td></tr>
<tr><td colspan="5">Lunch will be catered on site and generally scheduled between 12:00 to 1:00 each day although we may run 15 minutes ahead or behind on any given day.</td></tr>
<tr><td>Excursion to Steven F. Udvar-Hazy Center at the National Air & Space Museum</td><td>+10 Projects SPACE (cont.) & CYBER</td><td>ANNOTATING THE OUTLINE Part 1</td><td>Group writing time</td><td>Group writing time & Final Discussions (adjourn @ 3pm)</td></tr>
<tr><td>Dinner at NOSTOS in Tysons Corner</td><td>Informal Dinner gathering at Northside Social</td><td>Dinner at Rus Uz</td><td>Catered Dinner (Writing will continue into the evening)</td><td>Travel Safely :)</td></tr>
</table>