

ARTIFICIAL INTELLIGENCE AND THE SPACE ENTERPRISE: TAXONOMY AND EMERGING OPPORTUNITIES

Paul C. Frakes, Katherine E. Melbourne, Lauren H. Perry, Erik J. Linstead, and Andrew Brethorst

Artificial intelligence, or AI, is now a prominent part of the discourse on the future of space mission design and operations. Although the use of AI in space systems is not new, its influence is growing as AI technologies evolve and are integrated across more phases of the space mission lifecycle and in new applications. This paper defines AI terminology and underlying technologies as applicable to the space community, clarifies the distinction between AI and autonomy, and provides examples of missions and applications where AI is already having an impact across the space enterprise. The paper finds that this impact is uneven, and AI is likely to have the greatest effect in areas that involve analyzing large amounts of complex data. Maintaining U.S. leadership in space will depend more on how AI technologies are adopted and integrated than on the underlying AI technology itself.

Introduction

The use of artificial intelligence (AI) in space has emerged as a growing area of focus for policymakers and scholars in recent years. AI has been described as “critical” and “transformative” for many space applications (e.g., exploration, remote sensing, and space traffic management), and United States Space Force officials have indicated that the service is seeking to incorporate AI into its daily operations.^{1, 2} The vast potential of AI has spurred bold pronouncements about the future, with headlines and strategy documents describing AI as key to unlocking the space economy and to determining space dominance.^{3, 4}

Despite this attention, there is considerable confusion about the use of AI in space, even around basic questions of what it means, how it differs from existing technologies, and how it will affect space capabilities and

missions. For example, technologies that enable automation and autonomy in space are sometimes misconstrued as being “AI-driven,” despite representing distinct concepts.^{1, 5} The term is also overly broad because it encompasses a range of capabilities that differ in both type and complexity, from discrete tasks to layered decisionmaking. Amid this confusion, private companies are designing and marketing their products around AI capabilities or capabilities with AI components but without clear definitions or distinctions to compare the enhanced value or utility the addition of these capabilities presumes.

¹AI can enable autonomy. We discuss this further in the *Emerging Opportunities for Space* section, pointing out where AI is used or if *autonomy* would be a more accurate characterization of the current state of technology for a certain space application.

To give policymakers a clear foundation from which to evaluate and decide the appropriate role for AI in space, this paper first presents a practical lexicon of AI terms and technologies. Following that is a discussion of existing and emerging opportunities for application of AI technologies in critical space mission areas to address important space challenges. Where possible, an explanation is provided that defines the specific AI technology that is being used in a specific area. Finally, the conclusion offers some broad guidance for policymakers to navigate the confluence of space and AI.

A Practical Taxonomy for AI

The recent increased attention and focus on Generative AI (GenAI) applications such as ChatGPT and DeepSeek have led to the term *artificial intelligence* being applied broadly and loosely to include everything from web search and social media algorithms to hypothetical computational “singularities” that might bring about machines that surpass human intelligence.⁶ Just as cognitive scientists, biologists, philosophers, and information technologists all have different definitions for the word *intelligence*, the definition of AI varies as well.

A useful definition is found in 15 U.S. Code 9401(3): “[AI is] a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. Artificial intelligence systems use machine- and human-based inputs to perceive real and virtual environments; abstract such perceptions into models through analysis in an automated manner; and use model inference to formulate options for information or action.”⁷ Similarly, the Organization for Economic Cooperation and Development (OECD) defines not AI *itself* but an “AI system.” The outputs described are similar to those in the U.S. code, but the OECD emphasizes that “different AI systems vary in their levels of autonomy and adaptiveness after deployment.”⁸

AI technologies vary in complexity. Some are often described as *narrow* or *weak*, able to perform only one task well; *general* or *AGI* (artificial general intelligence) technologies are able to do many different tasks (on par with human intelligence); and *super* or *ASI* (artificial super intelligence) technologies reflect superhuman intelligence across many disciplines. A useful framework for

comparing the relative capabilities of AI systems is given by Morris, et al. of Google DeepMind (see Figure 1), blending elements of narrow, general, and ASI to describe an AI system’s capability relative to a human’s.⁹ Note that in these contexts, *intelligence* refers to the ability to reason and make conclusions based on disparate data inputs. There is ongoing debate within the community whether any of the current technologies will lead to *sentience*—i.e., self-awareness or cognition—which is often portrayed in science fiction.¹⁰

	Narrow	General
	Clearly scoped task or set of tasks	Wide range of tasks, including learning new skills
Level 0: No AI	Narrow Non-AI	General Non-AI
	Calculator software; compiler	Human-in-the-loop computing, e.g. Amazon Mechanical Turk
Level 1: Emerging AI	Emerging Narrow AI	Emerging AGI
Equal to or somewhat better than an unskilled human	Simple rule-based systems	ChatGPT, Llama 2, Gemini
Level 2: Competent AI	Competent Narrow AI	Competent AGI
At least 50th percentile of skilled adults	Toxicity detectors such as Jigsaw; smart speakers such as Siri, Alexa, or Google Assistant; LLMs for some tasks	Not yet achieved
Level 3: Expert AI	Expert Narrow AI	Expert AGI
At least 90th percentile of skilled adults	Spelling & grammar checkers such as Grammarly; image generators such as Imagen or Dall-E 2	Not yet achieved
Level 4: Virtuoso AI	Virtuoso Narrow AI	Virtuoso AGI
At least 99th percentile of skilled adults	Deep Blue, AlphaGo	Not yet achieved
Level 5: Superhuman AI	Superhuman Narrow AI	Artificial Superintelligence (ASI)
Outperforms 100% of humans	AlphaFold, AlphaZero, StockFish	Not yet achieved

Figure 1. An example framework for comparing AI capability. (Source: Morris et.al. 2023, reproduced with permission)

Core AI concepts are briefly defined below and an illustration of how those concepts relate to each other is seen in Figure 2. Widely used definitions of key AI terms are also found in the lexicon maintained by the Department of Defense’s Chief Digital and Artificial Intelligence Office (CDAO).¹¹

Expert systems seek to emulate the decisionmaking process of a human expert using a given body of knowledge, usually using a series of if–then rules that are hard-coded or inferred from data. Expert systems have been around since the 1970s. Beginning in 1985, NASA’s Johnson Space Center developed the C Language Integrated Production System (CLIPS) tool for developing expert systems.¹²

Machine learning (ML) is an application of AI that is characterized by providing systems the ability to automatically learn and improve on the basis of data or experience, without being explicitly programmed.

Supervised ML (or supervised learning) relies on pre-labeled data, with the goal of identifying new data according to the established patterns or rules.

Unsupervised ML uses unlabeled data, with the goal of identifying patterns within the data without *a priori* knowledge of the patterns. These are distinct from *reinforcement* ML in which the agent's learning is directed to maximize a tracked "reward" metric.

Neural network refers to a method that teaches computers to process data in a way that is inspired by the human brain. It is a type of machine learning process that uses interconnected nodes or neurons in a layered structure that resembles the human brain. A neural network creates an adaptive system that computers use to learn from their mistakes and improve continuously.

Deep learning (DL) is a subset of machine learning that can discover high-order features within data. DL involves using very large neural networks, with numerous layers and potentially billions of parameters, to automatically discover data patterns. DL techniques are inherently multimodal and can be easily adapted and applied to textual, audio, and imagery data, in addition to traditional tabular data.

Computer Vision (CV) is a field that aims to extract information from digital images, video, and other forms of visual input. Most modern-day CV applications leverage DL to perform tasks such as object identification, detection and tracking, and pixel-wise segmentation. Common approaches include deep convolutional neural networks and transformer-based models.

Natural language processing (NLP) sits at the intersection of linguistics, computer science, and AI. Its primary focus is to enable computers to recognize, understand, and generate text and speech via statistical and/or AI modeling. Applications in this field include (but are not limited to) information retrieval, knowledge representation, voice-operated systems (e.g., Amazon's *Alexa*), and digital assistants (e.g., Apple Inc.'s *Siri*).

Generative AI (GenAI) is a class of AI models that leverages deep learning to generate derived, synthetic content in response to complex and varied prompts.¹³ Such content includes text, audio, and visual data across many different languages and subjects. Today's high-profile applications such as OpenAI's *ChatGPT*, Meta's *Llama*, and Google's *Gemini* leverage a transformer neural network architecture (the "T" in ChatGPT). These networks consist of hundreds of layers with billions, if not trillions, of parameters and are commonly referred to as large language models (LLMs). Training an LLM from scratch requires enormous amounts of computing power, terabytes to petabytes of data, months of time, and millions of dollars—requirements often achievable only by a handful of the world's largest tech companies. However, there exist techniques that allow a practitioner to leverage an LLM and fine-tune it on a custom dataset using a fraction of compute power, thus making the barrier to entry much smaller for the ML community as a whole.

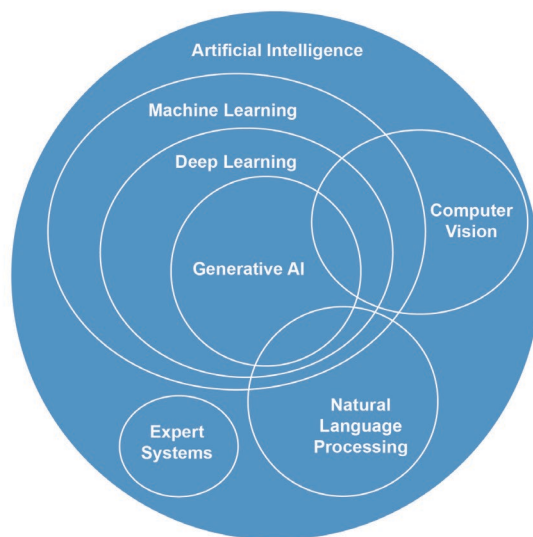


Figure 2. Pictorial representation of relationships among basic AI concepts.

Differentiating AI from Automation and Autonomy

AI is often used incorrectly as a synonym for autonomy, and both terms are often confused with automation. AI, autonomy, and automation are three distinct concepts, and understanding the differences between them is necessary

in order to precisely describe the requirements—and by extension, the design needs—of a particular mission.

Automation is an action or set of actions triggered by a stimulus based on pre-programming, often designed to be deployed repetitively in an unchanging environment. A robotic arm repeating a set of actions in a factory assembly line is an example of automation; it serves one function as part of a broader mission. Many early space systems included automated functions, such as the automatic picture-transmission system used to broadcast imagery from early weather satellites.^{14, 15} As reliance on both space and technology has progressed, space operations have grown increasingly dynamic and have revealed the inherent limits of relying on automation alone. As a result, there has been a shift toward incorporating more autonomy in space systems, the difference being a system’s capacity for increased adaptability to new stimuli while maintaining independent operations.

Autonomy refers to a machine system capable of operating at a certain degree of self-sufficiency from human control in a less predictable environment. For example, an autonomous robot can reach a target location in an environment with obstacles by using decisionmaking algorithms. The robot will also be able to apply the same algorithm and successfully navigate in similar environments with different obstacles and targets but, without AI, it does not learn or update its logic based on environmental input. As a result, the robot’s performance may be degraded in the face of unanticipated circumstances that develop over time.

For space systems, autonomy may be implemented at different scales—subsystem, spacecraft, or constellation—

and to varying extents within the system or system of systems. Different industries that employ autonomous systems have defined measurement schema to describe a system’s level of autonomy based on its dependence on humans; while the details of these schema are unique to each field, they span from limited implementation of automation at the lowest level to fully autonomous systems at the highest level. Researchers have proposed similar schema for defining the level of autonomy of a spacecraft.¹⁶

AI can enable even greater self-sufficiency by identifying and selecting the most optimal or efficient actions based on past training without human intervention. However, as seen in Figure 3, autonomy is not a necessary outcome of including AI in a system or process design; for example, AI could be employed specifically to aid humans (not machines) in decisionmaking.¹⁷ Still, there are a growing number of examples in which AI has been integrated into a system for the express purpose of increasing a system’s ability to make decisions and act without additional human intervention in a dynamic environment. On Earth, an example of a system utilizing AI to reach a level of autonomy in which human control is no longer needed is a self-driving car that can operate in complex, ever-changing conditions within a pre-defined geographic area. In space, an example system that integrates AI and autonomy is a remote sensing satellite using onboard AI models to autonomously determine which data to downlink first when there are constraints on downlink capacity.¹⁸ In both examples, an AI model is trained using data from past experiences to better respond to new situations in real time.

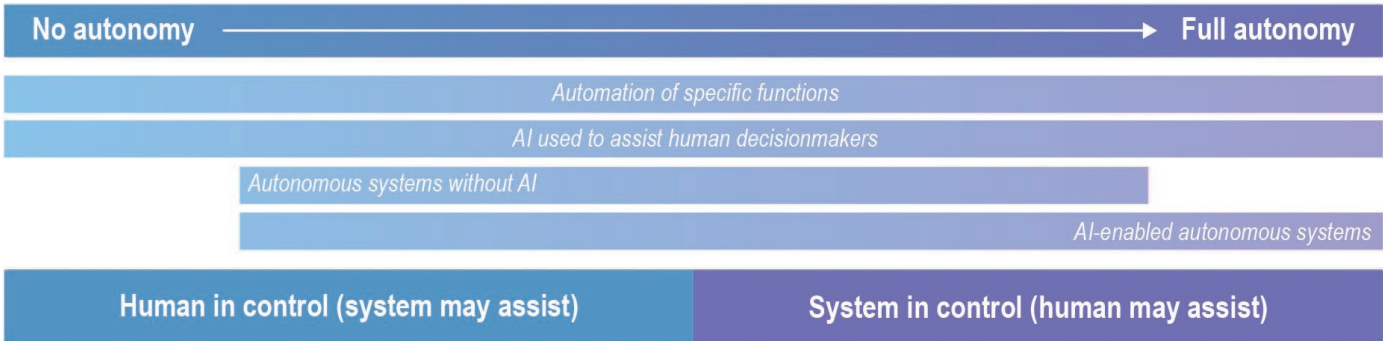


Figure 3: A system’s autonomy shown as a continuum and how automation and AI factor in decisionmaking.

Emerging Opportunities for Space

AI can support a space mission in every phase of its mission lifecycle, from system design to operation and system output analysis. Depending on the mission phase, the primary purpose of incorporating AI may change, and the effects can either be real-time, ongoing, or long term. Real-time effects of AI integration can include optimization—whether of time, resources, or quality—and system autonomy, allowing for self-directed, local decisionmaking onboard a satellite and improved responses to environmental stimuli. Increased interoperability of systems and their outputs is an example of a possible ongoing effect of using AI in space missions, as is assistance to humans interacting with the space system or its processes. Assistance from AI can alleviate human decision fatigue and help with routine tasks. While the recent popular enthusiasm for AI is mainly focused on GenAI technologies, the space enterprise has incorporated the broader set of AI technologies across different application domains. For example, government agencies and commercial companies alike have employed ML and DL systems for sensor data processing and analysis to extract additional insights from the growing amount of sensor data being produced by space systems. Efforts are also underway to explore the value of GenAI for augmenting human spaceflight operations. In 2024, an LLM was deployed onboard the International Space Station, believed to be the first time GenAI was deployed in space. This deployment was intended to demonstrate the feasibility of using GenAI to help astronauts solve problems locally rather than sending back large data sets to Earth for processing and analysis.¹⁹ The potential contributions of AI to space can be assessed by looking at its impact on each of the following mission areas.

Workforce Augmentation

AI tools are already used to streamline processes and increase automation across a project workflow, from design to operations.²⁰ For example, GenAI tools are projected to assist the broader workforce with routine tasks such as weekly reports, literature reviews, report writing, and other common writing tasks. The full range of AI technologies will also impact the space workforce at various stages, from education to manufacturing, on-orbit decisionmaking, and more. Thus, the next generation of the nation's workforce must be trained to use AI tools effectively in order to increase productivity, bolster

creativity, and keep pace with future aerospace industry needs. Organizations intent on future-proofing are harnessing AI tools that themselves can come up with new ways of solving problems—for example, NASA has demonstrated the ability of GenAI to develop innovative designs for mission parts.²¹ In terms of AI's ability to support on-orbit decisionmaking, it will be important to recognize opportunities as well as potential challenges. To that end, the U.S. Space Force is already working to identify space processes that are well-suited for AI use, as opposed to cases where there should always be a human-on-the-loop to engage with an otherwise autonomous system augmented by AI.²²

Remote Sensing

AI is also already being used to analyze space-based remote sensing data, which helps analysts identify myriad activities of interest ranging from illegal logging in the Amazon rainforest to military engagements in other parts of the world.^{23, 24} A review of the use of AI in remote sensing published in 2022 showed the wide-ranging applications of AI to the field, with a particular emphasis on the value of convolutional neural networks to AI-enabled remote sensing science.²⁵ As remote sensing data analysis can include various technological challenges (such as image description generation and image generation from sequential data), AI is useful to sort through these large data sets and quickly provide useful information to the end user. In 2025, Jet Propulsion Laboratory collaborated with two commercial organizations (Ubotica and Open Cosmos) to demonstrate combining AI and autonomy to show a proof of concept for a look-ahead sensor acquiring data and rapidly analyzing that data to drive subsequent observations.²⁶

Citizen science projects can also use remote sensing data combined with AI systems to promote sustainability and development around the world. Volunteer groups of citizen scientists have gathered and labeled plant data on the ground, which can then be combined with satellite imagery and used to train AI models that can monitor biodiversity in different ecosystems.²⁷ Disaster management is another area where citizen science, remote sensing, and AI make a powerful combination. Researchers have reduced uncertainty and improved the data resolution of satellite images used in high-tide flood monitoring initiatives by combining remote sensing data with data provided by volunteers through computer-vision

algorithms.²⁸ As another example, in the case of a forest fire, remote sensing satellites may not only be able to detect the onset of a fire but also sense characteristics that could *prompt* a fire, such as the drying of forests or the large presence of species of trees that might be more flammable than others. Synthetic aperture radar satellites can help measure the biomass in vegetation; the resulting data can then help model fuel availability and map the likely spread of a potential wildfire. AI tools can analyze the data much more quickly than humans could unassisted, resulting in overall improvements in fire prevention and fire response.

Astronomy and Planetary Exploration

Civil space agencies have employed AI applications to facilitate scientific research in astronomy and cosmology. AI image recognition capabilities are being used to coordinate telescopes in order to mine and analyze huge amount of incoming astronomy data.²⁹ For example, discovering exoplanets—planets orbiting distant stars—requires scientists to sift through extensive datasets of candidate planet observations to separate true exoplanets from false positives. To help with this process, NASA developed a deep neural network called *ExoMiner* by training the tool on the characteristics of a false positive exoplanet observation. When applied to a catalogue of 100,000 candidate signals, *ExoMiner* quickly and precisely validated 301 new exoplanets.³⁰

AI is also being used to help resolve space domain challenges created by communications gaps or constraints. NASA’s Automated Scheduling and Planning Environment (ASPEN) tool can help translate high-level objections into low-level commands suitable for constrained communications environments such as deep space probes and communications antennae.³¹ AI is also providing additional autonomy in extraterrestrial exploration on Mars to help NASA rovers accomplish more in less time. The *Perseverance* rover’s spectrometer is using AI to autonomously determine which rocks and mineral samples are worth examining more deeply, while *Curiosity* uses AI to help it navigate without direct instructions from Earth.³²

Space Situational Awareness/Space Domain Awareness

Assessing the state of the space environment requires the collection and fusion of hundreds of thousands of data

points consisting of unintuitive, latent, biased, noisy, and inconsistent data from many different types of sensors. Both space situational awareness (SSA), defined as overall awareness of the space environment,³³ and its subcomponent, space domain awareness (SDA), which is understanding and predicting the operational environment,³⁴ have found AI useful for object identification, tracking, and pattern of life characterization, even if traditional deterministic algorithms are still the mainstay.

Researchers have focused on identifying AI techniques to classify a satellite’s “patterns of life” at different orbital regimes,² typically using either supervised or unsupervised ML.^{35, 36} A recent example of this includes efforts by the Defense Advanced Research Projects Agency to develop *Agatha*, a tool that seeks outliers within constellations of satellites.³⁷ Additionally, AI can be applied to optimize the tasking of sensors, untangling signals from different space objects, orbit determination propagation, and SDA catalog maintenance.³⁸ By assessing historical data, AI has also been useful in developing early warning criteria for space weather events—a critical aspect of SDA.³⁹ One area of ongoing work to improve the use of AI for SDA is the creation of quality, labeled data and accurate, physics-based models of spacecraft and their orbits.⁴⁰

Space Traffic Management

The rapid increase in the number of space objects orbiting the Earth has prompted a growing focus on space traffic management (STM), also known as space traffic coordination (STC), which the U.S. government has defined as planning, coordination, and on-orbit synchronization of activities to enhance the safety, stability, and sustainability of operations in the space environment.⁴¹ Generally, AI has not been applied to STM.

However, as the number of satellites—in particular, large constellations of thousands of satellites—increases, the number of close approaches that could potentially result in collisions grows exponentially. Satellite operators routinely must perform conjunction assessments (CAs) and calculate the most appropriate risk mitigation maneuvers (RMMs) to alter a satellite’s trajectory and

² *Patterns of life* describe a satellite’s usual behavior, including station keeping maneuvers, and when well-characterized, demonstrate a satellite’s compliance with existing standards, norms, and regulations.

reduce the probability of a collision. Large satellite constellations are increasingly performing autonomous CAs and RMMs, but at the moment these techniques are not AI-driven but are based on classic deterministic algorithms. This is mainly due to the lack of real-world data on which events, of the many thousands of close approaches, would have resulted in actual collisions—information that would be needed to train an AI model. However, these limitations may be overcome as space agencies and startups continue to explore the use of AI and ML for future flight safety applications.^{42, 43}

In-Space Servicing, Assembly, and Manufacturing

In-space servicing, assembly, and manufacturing (ISAM) technologies are poised to change the satellite industry with capabilities like satellite refueling, in-space assembly of large structures, and in-space additive manufacturing.⁴⁴ AI technologies play an important role in advancing this ISAM technology. For example, satellites can use onboard cameras combined with traditional algorithms trained by AI to perform autonomous rendezvous, proximity operations, and docking.⁴⁵ The currently limited computational power of onboard, radiation-hardened electronics will likely mean algorithms are developed on the ground using training data, fine-tuned with operational data post-launch, and then implemented in space. However, researchers are actively working to overcome this onboard computation limitation.^{46, 47} Additionally, some researchers are developing AI on-orbit assembly planning systems that overcome the need for real-time, remote-controlled assembly from human operators, enabling ISAM operations that are responsive to real-time feedback.⁴⁸

Security

One area of active research is on how AI can be used to build more effective defenses capable of detecting and responding to threats against space systems. Research suggests encryption enhanced by AI could preempt attacks by scaling satellite and ground station security measures to outpace constantly evolving threats.⁴⁹ Cybersecurity experts are also developing advanced AI-driven “intrusion detection systems” to identify and address vulnerabilities.⁵⁰ On the responsive end, ML is being applied to adapt signal transmission in real time to prevent accidental interference and intentional jamming of satellite communication links.⁵¹ These examples span the entire threat lifecycle but are connected by a common theme: AI

applications can be used to boost autonomy within a system or process, enabling faster and more optimal decisions, and by extension, more secure space systems.

Conclusion

As the United States looks to strengthen its space capabilities to meet new global challenges, policymakers must look beyond just the AI label and investigate which specific AI technologies are being employed and how. The field of AI has been around for decades and encompasses a broad range of techniques, each with its own unique advantages and requirements. For greater effect, the space community needs to refrain from speaking in generalities about “using AI” but rather specify *which* AI technology is being used and *what* particular problem the AI is addressing. Doing so can avoid wasting taxpayer dollars chasing marketing hype and going down fruitless dead ends.

This paper also illustrates how AI tools and processing techniques can offer advantages across multiple space missions, but those advantages have been uneven. Of the areas examined here, remote sensing demonstrates the widest current adoption of AI tools, along with NASA’s emerging use of AI for astronomy and planetary exploration. The common thread among the two areas is that they both involve analyzing large amounts of complex data, a critical requirement for training effective AI algorithms and a class of problems that AI techniques are well-suited to analyzing. The potential for AI in workforce augmentation certainly shows promise as it crosscuts many sectors of industry. For example, for space traffic management and SSA/SDA, AI could scale our ability to monitor, coordinate, and predict the trajectory of objects in orbit to meet future demand. AI technology could also help realize the economic benefits from future ISAM capabilities that unlock sustainable economic development in space. Finally, the threat environment in space is evolving at a rate that will necessitate the use of AI for enhanced security. However, multiple barriers to adoption exist from a cultural and knowledge sharing basis, as well as continuity of operations and services.

Maintaining U.S. leadership in space and in the services space provides will require continued investment in and development and deployment of effective AI solutions, as well as seeking new opportunities to leverage AI to help

maintain that advantage. Researchers have found that the choices countries make in how they adopt and use new technologies matters much more than the technologies themselves.⁵² To this effect, future research must tease out how to test, verify, and build trust in systems that use AI. Analysis is needed to understand the risks of integrating AI into space operations and the extent to when humans-on-the-loop will still be needed. Ultimately, decisionmakers will need to take all of this information into account in deciding how to shape AI governance to maximize its potential and minimize the risks. The foundation for approaching these open questions is built on AI literacy, and this paper introduces the important considerations for AI's current and future impact on the space industry.

References

- ¹ The Critical Role of AI in Space Exploration - Newsweek; Project MUSE - The Use of Artificial Intelligence in Outer Space Capabilities.
- ² Space Force wants to weave AI into everyday operations - SpaceNews.
- ³ AI Is Unlocking The Multi-Trillion Dollar Space Economy; Why AI Mastery Determines Space Dominance.
- ⁴ USSF Data and AI FY2025 Strategic Action Plan.pdf
- ⁵ Fong, Terry, "Autonomous Systems: NASA Capability Overview", NASA, slide 8, August 24, 2018, https://www.nasa.gov/wp-content/uploads/2015/03/nac_tie_aug2018_tfang_tagged.pdf.
- ⁶ Scott Rosenberg, "In tech, everything is AI now" *Axios* (June 20th, 2023) <https://www.axios.com/2023/06/20/ai-everything-definition-label-hype>.
- ⁷ Title 15 US Code, Section 9401. [https://uscode.house.gov/view.xhtml?req=\(title:15%20section:9401%20edition:prelim\)](https://uscode.house.gov/view.xhtml?req=(title:15%20section:9401%20edition:prelim)).
- ⁸ Grobelnik et al., "What is AI? Can you make a clear distinction between AI and non-AI systems?," March 6, 2024. <https://oecd.ai/en/wonk/definition>.
- ⁹ Morris et al., "Levels of AGI for Operationalizing Progress on the Path to AGI," 2023. <https://arxiv.org/pdf/2311.02462>.
- ¹⁰ Ashley, Michael, "AI is Acting Like It Has a Mind of Its Own", *Forbes*, July 29, 2025, <https://www.forbes.com/sites/michaelashley/2025/07/29/ai-is-acting-like-it-has-a-mind-of-its-own/>.
- ¹¹ CDAO Lexicon. <https://www.ai.mil/Lexicon>.
- ¹² "CLIPS: A Tool for Building Expert Systems," Retrieved Aug 15, 2025. <https://www.clipsrules.net/>.
- ¹³ Lim et al., "Generative AI and the future of education: Ragnarök or reformation? A paradoxical perspective from management educators," July 2023. <https://www.sciencedirect.com/science/article/pii/S1472811723000289>.

- ¹⁴ Excerpt from page 3, "the system is completely automatic and requires no ground commands for operation," ntrs.nasa.gov/api/citations/19680010155/downloads/19680010155.pdf.
- ¹⁵ For additional examples, see Project MUSE - The Use of Artificial Intelligence in Outer Space Capabilities.
- ¹⁶ Baker, Daniel, and Phillips, Sean, "Spacecraft Autonomy Levels," 2 March 2025, <https://arxiv.org/abs/2503.01049>.
- ¹⁷ Feng, Kevin J. et al., "Levels of Autonomy for AI Agents", *Arxiv*, July 28, 2025, <https://arxiv.org/pdf/2506.12469>.
- ¹⁸ Goodwill et al., "Current AI Technology in Space," NASA GSFC, July 2023. <https://ntrs.nasa.gov/api/citations/20240001139/downloads/Current%20Technology%20in%20Space%20v4%20Briefing.pdf>.
- ¹⁹ "ISS National Lab-Sponsored Experiments Propel Spaceborne Computer Toward New Frontiers in Space Computing," Jan 23, 2024. <https://issnationallab.org/press-releases/release-ng20-hpe-spaceborne-computer2/>.
- ²⁰ Plathottam et al., "A review of artificial intelligence applications in manufacturing operations," *Journal of Advanced Manufacturing and Processing*, May 16, 2023. <https://aiche.onlinelibrary.wiley.com/doi/full/10.1002/amp2.10159>.
- ²¹ K. Hille, "NASA turns to AI to design mission hardware," Feb 9, 2023. <https://www.nasa.gov/technology/goddard-tech/nasa-turns-to-ai-to-design-mission-hardware/>.
- ²² "USSF Paused AI Adoption in '23; Now It's Looking to Automate Ops," Feb 26, 2025. <https://www.airandspaceforces.com/space-force-from-ai-pause-to-satellite-ops/>.
- ²³ Mark Hillsdon, "From forest-listening to advanced remote sensing, can AI turn the tide on deforestation?" *Reuters*, Jan. 16, 2024. <https://www.reuters.com/sustainability/land-use-biodiversity/forest-listening-advanced-remote-sensing-can-ai-turn-tide-deforestation-2024-01-16/>.
- ²⁴ "GEOINT Artificial Intelligence," Retrieved Aug 15, 2025. https://www.nga.mil/news/GEOINT_Artificial_Intelligence_.html.
- ²⁵ Lefei Zhang and Liangpei Zhang, "Artificial Intelligence for Remote Sensing Data Analysis," *IEEE Geoscience and Remote Sensing Magazine*, June 2022. <https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9756442>.
- ²⁶ Chien et al., "Flight of Dynamic Targeting on CogniSAT-6 – Update," May 2025. <https://ai.jpl.nasa.gov/public/documents/papers/dt-spaceops-2025.pdf>.
- ²⁷ Golparvar et al., "AI-supported citizen science to monitor high-tide flooding in Newport Beach, California," Nov. 3, 2020. <https://dl.acm.org/doi/10.1145/3423455.3430315>.
- ²⁸ Ibid.
- ²⁹ Allison Snyder, "Astronomers are using AI to study the vast universe – fast," *Axios* (January 11th, 2018), <https://www.axios.com/2018/01/11/astronomers-are-using-ai-to-study-the-vast-universe-fast-1515610061>.
- ³⁰ Valizadegan et al., "ExoMiner: A Highly Accurate and Explainable Deep Learning Classifier That Validates 301 New Exoplanets," Feb. 17, 2022.

<https://iopscience.iop.org/article/10.3847/1538-4357/ac4399/meta>.

³¹ “ASPEN,” NASA Jet Propulsion Laboratory. <https://ai.jpl.nasa.gov/public/projects/aspenn/>.

³² NASA, “Here’s How AI Is Changing NASA’s Mars Rover Science,” Jul 16, 2024. <https://www.nasa.gov/missions/mars-2020-perseverance/perseverance-rover/heres-how-ai-is-changing-nasas-mars-rover-science/>.

³³ <https://csp.aerospace.org/papers/space-traffic-management-terminology>.

³⁴ <https://aerospace.org/ssi-space-situational-awareness>.

³⁵ Siew et al., “AI SSA Challenge Problem: Satellite Pattern-of-Life Characterization Dataset and Benchmark Suite,” 2023. <https://amostech.com/TechnicalPapers/2023/Machine-Learning-for-SDA/Siew2.pdf>.

³⁶ Guimaraes et al., “Data-Driven Identification of Main Behavioural Classes and Characteristics of Resident Space Objects in Low Earth Orbit through Unsupervised Learning,” 2024.

<https://amostech.com/TechnicalPapers/2024/Poster/Guimaraes.pdf>.

³⁷ DARPA harnesses AI to keep tabs on space weapons, spy satellites on orbit | DefenseScoop.

³⁸ Zhang et al., “Artificial Intelligence and Machine Learning for Space Domain Awareness,” Nov 21, 2024. https://www.rand.org/pubs/research_reports/RRA2318-1.html.

³⁹ Feng et al., “PreMevE-MEO: Predicting Ultra-Relativistic Electrons Using Observations From GPS Satellites,” Sept 28, 2024.

<https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2024SW003975>.

⁴⁰ Tony McDevitt, “Is AI the next frontier in spacecraft design, or just a shiny buzzword?” Jun 13, 2025.

<https://spacenews.com/is-ai-the-next-frontier-in-spacecraft-design-or-just-a-shiny-buzzword/>.

⁴¹ Space Policy Directive-3, National Space Traffic Management Policy, June 18, 2018.

<https://csp.aerospace.org/sites/default/files/2021-08/Space%20Policy%20Directive%203%20-%20STM%2018Jun18.pdf>.

⁴² T. Uriot, D. Izzo, L. Simões, R. Abay, N. Einecke, S. Rebhan, J. Martinez-Heras, F. Letizia, J. Siminski, K. Merz. Spacecraft collision Avoidance challenge: Design and results of a machine learning competition. *Astrodynamics* 6, 121–140, 2022.

⁴³ Ravi et al., “AI for Satellite Collision Avoidance—Go/No Go Decision-Making,” 2023.

<https://www.hou.usra.edu/meetings/orbitaldebris2023/pdf/6043.pdf>.

⁴⁴ In-Space Servicing, Assembly, and Manufacturing (ISAM), NASA, Accessed July 8, 2025. <https://www.nasa.gov/nexis/isam/>.

⁴⁵ SpaceNews, “Space Loves AI – How AI Promises to Transform Space Operations.” Webinar. Published May 16, 2024. <https://www.youtube.com/watch?v=fljCMjveZZs>.

⁴⁶ Taquichiri et al., “Achieving Dependability of AI Execution with Radiation Hardened Processors,” Mar. 21, 2025. <https://arxiv.org/abs/2504.03680>.

⁴⁷ Noah Perryman et al., “SpaceCube GHOST: A Resilient Processor for Low-Power, High-Reliability Space Computing,” 2020 IEEE Aerospace Conference.

<https://ieeexplore.ieee.org/document/10521244>.

⁴⁸ David Timmermann et al., “AI-Based Assembly Sequence Planning in a Robotic On-Orbit Assembly Application,” 2024. <https://ieeexplore.ieee.org/abstract/document/10553031>.

⁴⁹ AI-Powered Data Encryption Techniques: Safeguarding Cloud Infrastructure | IEEE Conference Publication | IEEE Xplore.

⁵⁰ AI-Powered Network Intrusion Detection: A New Frontier in Cybersecurity | IEEE Conference Publication | IEEE Xplore

⁵¹ 20190001548.pdf.

⁵² Michael Horowitz, “Artificial Intelligence, International Competition, and the Balance of Power,” Texas National Security Review, Vol 1, Issue 3, pp. 36-57, May 2018. <https://tnsr.org/2018/05/artificial-intelligence-international-competition-and-the-balance-of-power>.

About the Authors

Paul C. Frakes is a systems engineer and certified foresight practitioner in the Center for Space Policy and Strategy at The Aerospace Corporation. In this role he leads horizon-scanning efforts to find new signals of change across a variety of disciplines and topic areas and applies foresighting methods and tools to derive unique insights, helping customers challenge their assumptions and make more resilient investments. In previous roles at Aerospace, he performed international technology assessments, resiliency analysis, and smallsat risk assessments. Prior to joining Aerospace, his work included performing realtime conjunction risk assessments for NASA, helping to protect more than 60 operational satellites from on-orbit collisions. Frakes holds a bachelor's degree in aeronautical and astronautical engineering from Purdue University and a master's degree in systems engineering from Johns Hopkins University.

Katherine E. Melbourne is a national security space analyst at The Aerospace Corporation's Center for Space Policy and Strategy. She previously worked in the aerospace industry as a systems engineer on the James Webb Space Telescope commissioning team and translated cislunar mechanics to an educational wargame for the U.S. Space Force. Melbourne received her bachelor's degree from Yale University in astrophysics and her master's degree in aerospace engineering from the University of Colorado Boulder.

Lauren H. Perry is a senior project engineer in the Space Applications Group at The Aerospace Corporation. Her work incorporates AI/ML technologies into traditional software development programs for the intelligence community, DOD, and commercial customers. Previously, she was the analytical lead for a DOD project established to improve joint interoperability within the Integrated Air and Missile Defense (IAMMD) Family of Systems and enhance air warfare capability. Perry was also a reliability engineer at Lockheed Martin Space Systems Company. She has a background in experimental design, applied statistics, and statistical engineering for the aerospace domain.

Erik J. Linstead is a member of the Data Science and Artificial Intelligence Department at The Aerospace Corporation, as well as a professor of computer science and software engineering at Chapman University in Orange, CA. His research interests span all areas of machine learning, but he considers his most important work to be at the intersection of machine learning and autism spectrum disorder, where he has published extensively. Linstead holds a doctorate from the University of California, Irvine, a master's degree from Stanford University, and a bachelor's degree from Chapman University, all in computer science. He is also a senior member of the Association for Computing Machinery and the Institute of Electrical and Electronic Engineers.

Andrew Brethorst is a senior engineering specialist in the Data Science and Artificial Intelligence Department at The Aerospace Corporation. Brethorst received his bachelor's degree in cybernetics from the University of California, Los Angeles, and later earned his master's degree in computer science with a concentration in machine learning at the University of California, Irvine. Much of his work involves applying machine learning techniques to image exploitation, telemetry anomaly detection, and intelligent artificial agents using reinforcement learning, as well as collaborative projects within Aerospace's research labs.

About the Center for Space Policy and Strategy

The Center for Space Policy and Strategy is dedicated to shaping the future by providing nonpartisan research and strategic analysis to decisionmakers. The Center is part of The Aerospace Corporation, a nonprofit organization that advises the government on complex space enterprise and systems engineering problems.

The views expressed in this publication are solely those of the author(s), and do not necessarily reflect those of The Aerospace Corporation, its management, or its customers.

For more information, go to www.aerospace.org/policy or email policy@aero.org.

© 2025 The Aerospace Corporation. All trademarks, service marks, and trade names contained herein are the property of their respective owners. Approved for public release; distribution unlimited. OTR202501155



csps.aerospace.org