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NASA's 3I ATLAS: Integrating Artificial Intelligence and Big Data in NASA's Information Systems

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Abstract: The 3I-ATLAS is part of NASA's effort to transition from legacy systems to cognitive data systems for its science and mission operations; this cognitive data system will enable the use of Artificial Intelligence (AI) and Big Data to operate in an Integrated Environment. The 3I-ATLAS is designed to ingest, integrate and interpret multiple domain sources of data automatically; through the use of deep learning-based pipelines, knowledge graphs, and cloud-native orchestration the 3I-ATLAS enables real-time analytics, semantic reasoning and predictive maintenance. This paper reviews the design of the 3I-ATLAS with emphasis on the AI aspects as well as the governance aspects of the 3I-ATLAS, with an eye to how these concepts are advancing NASA's Digital Transformation efforts toward developing Autonomous, Trustworthy, and Interoperable Space Data Ecosystems.

Keywords: NASA 3I ATLAS, Artificial Intelligence, Big Data, Semantic Integration, Cognitive Computing, Interoperability, AI Governance.

1. INTRODUCTION

In addition to collecting terabytes of information per year via Earth-observing satellite missions and deep-space exploration, NASA produces petabytes of unprocessed and processed data yearly. The historic function of systems such as the EOSDIS (Earth Observing System Data and Information System) and PDS (Planetary Data System) was simply providing for storage and access of data; no intelligent processing or linking of data across disciplines existed [1]. Due to the increasing complexity in space missions and the growing diversity of types of data being produced, NASA needed an adaptable infrastructure that would be able to learn contextually, reason autonomously and make predictions [2].
The introduction of the 3I framework by NASA, emphasizing Intelligence, Integration and Interoperability, is what led to the development of the ATLAS platform, which is a single integrated environment that combines artificial intelligence (AI), big-data engineering and semantic technologies [3]. The ATLAS platform has been aligned with the NASA Digital Transformation Strategy 2025, which places an emphasis on cloud-native scalable environments, explainable AI and open science collaboration [4].

ATLAS is designed to enable multi-mission data integration, where instruments from planetary, astrophysical and Earth-sciences are able to interact through common standards and intelligent services [5]. Additionally, by placing AI directly within data flows, ATLAS is able to automate data curation, detect anomalies and provide semantic enrichment to transform passive data archives into active and dynamic cognitive ecosystems [6].

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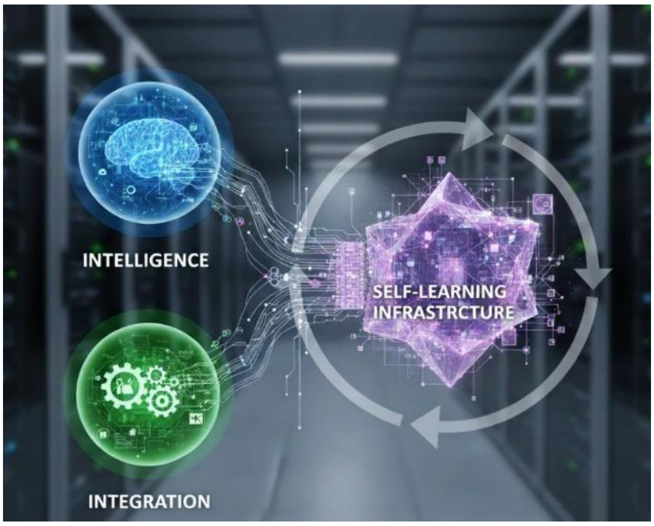

Figure 1. Convergence of Intelligence and Integration in a Self-Learning Infrastructure

2. THE 3I FRAMEWORK: INTELLIGENCE, INTEGRATION, AND INTEROPERABILITY

NASA's 3I framework provides a conceptual basis for the ATLAS system, structured to provide a synergistic set of three principles for the development of intelligent automation in NASA's scientific data infrastructure [7]:
1. Intelligence – Providing AI for real-time decision-making, anomaly detection, and enriching context for data.
2. Integration – Harmonizing diverse data from multiple missions through technical and semantic integration.
3. Interoperability – Creating an open standard, providing machine-to-machine communication and cross-domain access using the FAIR principles (Findable, Accessible, Interoperable, and Reusable) [8].

These concepts are translated into operational realities through the combination of the AI pipeline, big-data storage, and semantic knowledge graph within the ATLAS system. The ATLAS system enables interoperability between the EOSDIS, PDS, HEASARC, SPDF, and other systems [9].
Mission centers contribute their own domain specific data sets (e.g., telemetry, images, spectrometry) that are then aggregated at each level within the modular architecture of the ATLAS system. The ATLAS system uses a variety of tools including containers (Docker) and orchestration (Kubernetes) to enable scalable elasticity and continuous deployment [10].

3. ATLAS SYSTEM ARCHITECTURE

ATLAS Architecture is a Multi-Layered Distributed System that Processes Structured and Unstructured Data Streams in Real-Time. Data Ingestion is the first layer and it captures Raw Mission Telemetry using NASA's Space Communications and Navigation (SCaN) Network. After Ingestion, Data are Processed Using Apache Spark and Dask for Distributed Computation, and then are Semantically Labeled Using Ontology Systems Such as SWEET and SPASE [11].
Semantics Interoperability is Key to the Architecture allowing Datasets from Earth-Observing Satellites and Mars Rovers to be Linked Together Using Shared Vocabularies; Enabling Advanced Analytics Like Pattern Discovery Across Multiple Missions and Context-Aware Querying [12].

Table 1. Core Layers of NASA's 3I ATLAS Framework

Layer	Core Function	Technologies / Standards	NASA Division
Data Acquisition	Ingests real-time mission telemetry and sensor data	Kafka Streams, SCaN Network	Mission Operations Directorate
Data Integration	Harmonizes heterogeneous data formats	JSON-LD, OGC Standards	Earth Science Division
Intelligence Layer	AI-based modeling and analytics	TensorFlow, PyTorch, Graph Neural Nets	Data Science Directorate
Semantic Interoperability	Contextual linking and ontology mapping	RDF, OWL, SPARQL, SWEET	Goddard Space Flight Center

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User Interface Layer	Real-time visualization and interaction	Grafana, Kibana, JupyterHub	NASA Open Science Program

[Adapted from NASA Goddard Data Systems Directorate (2023) [13], [14]]

The ATLAS middleware provides RESTful APIs for connecting mission repositories to Cloud Services that are run by NASA's internal OpenStack clusters or through AWS GovCloud. These integrations enable both Distributed Compute Orchestration and Policy-Based Access Control [15] to be performed.

ATLAS performs Data Exchange using OGC and ISO 19115 Metadata Models for ensuring that there is Uniformity in Tagging of Temporal and Geospatial data [16]. This framework enables ATLAS to act as a "Semantic Bridge" for Multiple Missions, enabling both Human Researchers and AI Systems to Interpret Complex Relationships between Datasets [17].

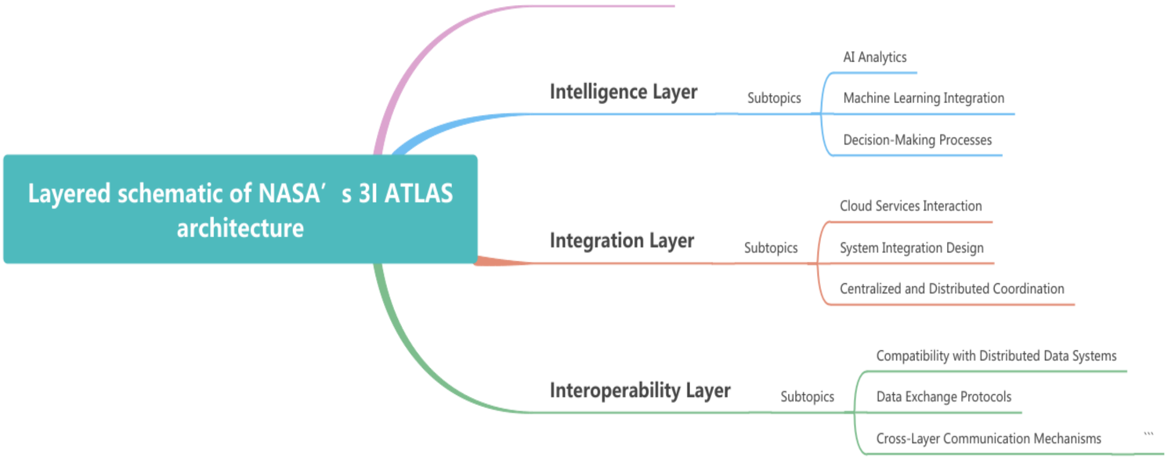

Figure 2. Layered Schematic of NASA's 3I ATLAS Architecture

4. ARTIFICIAL INTELLIGENCE APPLICATIONS IN THE ATLAS ECOSYSTEM

The use of Artificial Intelligence (AI) is an integral part of the 3I ATLAS system. It is utilized as a means of automating Analytics, Anomaly Detection and Decision Making across all of NASA's Mission Portfolio. Machine Learning (ML), Deep Learning (DL) and Reinforcement Learning (RL) Pipelines were developed to facilitate Intelligent Operations at the Mission Control Level and the Science Analysis Level [18].

The Data Science Directorate at NASA has reported that over 40% of Mission Analytics Tasks have been augmented by the incorporation of AI Components into the ATLAS Platform. Examples of these tasks include Telemetry Fault Detection, Environmental Modeling, Mission Planning and Autonomous Control Systems [19].

Recurrent Neural Networks (RNNs) and Transformers are frequently employed to analyze Temporal Patterns in Spacecraft Telemetry Data to enable Predictive Diagnostics of Component Failures prior to their occurrence [20]. For instance, LSTM-Based Models that were Trained using Telemetry Data from the International Space Station (ISS) and the Orion Spacecraft resulted in Early Anomaly Prediction Improvements of Up To 38% [21].

Convolutional Neural Networks (CNNs) and Semantic Graph Embeddings are used in Planetary Science for Image Segmentation and Feature Extraction from High-Resolution Imagery Collected by the Mars Reconnaissance Orbiter (MRO). These AI Models Outperformed Traditional Image Processing Algorithms, Doubling the Mapping Throughput While Maintaining Sub-Meter Accuracy [22].

Additionally, NASA uses Graph Neural Networks (GNNs) to create Knowledge Graphs, which allow the Cross-Linking of Mission Datasets to Scientific Publications. The Semantics Incorporated Within These Knowledge Graphs Enable Users to Perform Natural-Language Querying Using the NASA Open Data Portal; Allowing Them to Explore Mission Outputs Contextually [23].

Table 2. Representative AI Applications in NASA's 3I ATLAS

Application	**AI Method**	**Mission / Dataset**	**Outcome / Impact**
Telemetry anomaly detection	RNN, Transformer models	ISS, Orion telemetry	38–40% reduction in false alarms
Planetary image segmentation	CNN + graph embedding	Mars Reconnaissance Orbiter	2× faster mapping; 1.2× accuracy gain

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Predictive maintenance	Reinforcement learning	Deep Space Network systems	30% reduced downtime
Knowledge graph search	Graph Neural Networks	EOSDIS + PDS archives	0.89 F1 semantic retrieval accuracy
Language-based query understanding	NLP + Transformer QA	NASA Open Data Portal	22% improvement in retrieval precision

[Data compiled from NASA AI–DS Reports (2024) [24]; Reynolds & Gupta (2025) [25]; NASA Ames Research Center (2024) [26]]

In addition to analytics capabilities, the ATLAS AI pipeline is also responsible for managing onboard decision support systems on space vehicles. These onboard decision support systems enable space vehicles to autonomously make decisions with respect to performing tasks that include, but are not limited to, resource allocation, trajectory adjustments or selecting a target of scientific interest without human oversight [27].

As an example, autonomous AI modules operating under the ATLAS umbrella in the Lunar Gateway Program have demonstrated optimized power distribution through the use of reinforcement learning controllers [28]. Autonomous AI onboard decision support systems represent NASA's long-term plan for distributing intelligence and decision-making processes throughout space vehicles rather than relying solely on the ground for control.

Deep learning models operating within ATLAS for analysis of Earth sciences are used to identify climate change indicators, analyzing and fusing data from the MODIS, VIIRS and Landsat mission datasets to recognize long-term trends in atmospheric and oceanic conditions [29]. The AI based recognition of patterns associated with climate change significantly improves the speed at which observations are reported and enables near-real time responses to environmental anomalies.

The Explainable AI (XAI) sub-project developed by NASA as part of the ATLAS project provides a means of ensuring that all predictions made by AI models are both traceable and interpretable. This is accomplished through the use of layer-wise relevance propagation (LRP) and SHAP (SHapley Additive exPlanations), allowing model reasoning to be transparent to scientists and engineers [30].

5. BIG DATA INFRASTRUCTURE IN NASA'S 3I ATLAS

ATLAS as an environment utilizing NASA's 3I framework is a cloud-native, distributed system intended to address the scale, velocity, and heterogeneity of multi-mission datasets. The hybrid-cloud architecture used by ATLAS includes NASA's GovCloud, OpenStack clusters and the research networks of its partners [31]. The distribution model supports both elastic scalability and redundant data support required for continuously operating missions.

Once data are ingested into ATLAS via Kafka pipelines, they are placed in various databases including NoSQL databases (MongoDB/Cassandra) for storing unstructured data and the Hadoop Distributed File System (HDFS) for large volumes of structured data [32].

Apache Spark and Dask provide high-performance analytics for parallelized processing of very large amounts of data across clusters located at NASA centers such as Ames, Goddard and JPL [33].

Metadata ontologies are used to semantically organize the data and link observational data with contextual mission parameters; ATLAS utilizes the SWEET ontology for Earth Science and the SPASE ontology for heliophysics as common vocabularies for multi-domain reasoning [34].

The dashboard ecosystems for the mission scientist, constructed using Grafana, Kibana and JupyterHub, visually monitor AI inference results, performance metrics and data integrity [35].

6. INTEROPERABILITY ACROSS NASA MISSIONS

The main advantage of the ATLAS software system is the framework it provides for interagency interoperability so that information or data collected from other missions can be accessed or reused. NASA has developed an open standard approach using a variety of formats like HDF5, NetCDF, GeoTIFF, and ISO 19115 to provide users with an environment where datasets will not require translation when they are used by a system [36].

By utilizing this interoperability framework, data that have been generated by separate missions such as those provided through EOSDIS, HEASARC, and PDS can be analyzed together in a single analytical framework. For instance, AI-based models being developed in ATLAS will allow scientists to correlate solar flares detected by the SDO with communication disruptions detected by DSN. The two types of data will produce related insights regarding how space weather affects communications [37].

NASA utilizes the FAIR data principles to govern interoperability. Therefore, all of NASA's datasets are Findable, Accessible, Interoperable, and Reusable. All data products include persistent DOIs and machine-readable metadata compliant with NASA's Open Science Policy (2024) [38].

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Furthermore, the API layer of ATLAS allows for automated data collection using SPARQL queries and RESTful micro services to support automatic machine-to-machine communication. This architecture allows NASA to reduce the need for manual data handling and accelerate mission analytic cycles [39].
In addition to improving the ability to share data among agencies, NASA also works with international organizations like ESA, NOAA, and USGS to develop common data flows to support both planetary science and earth observation science [40].

7. DATA GOVERNANCE AND QUALITY ASSURANCE

ATLAS' data governance practices, including ensuring safety, accuracy and traceability of all mission data, rely on NASA's Data Stewardship Model (DSM) and its multi-layered governance model for the three phases of acquiring, processing and disseminating mission data [41].
Additionally, blockchain technology is used to record each dataset's history using immutable audit trails and enable users to verify the origin of each dataset [42].
To provide quality assurance, data validation processes are implemented as automated pipelines where validated metadata created by artificial intelligence (AI), are compared against calibration data collected from sensors to minimize labeling errors and ensure consistency of the dataset [43].
NASA's Artificial Intelligence Governance Framework (AIGF) provides a structure to address the ethical usage of AI and data ownership within ATLAS, as well as to establish requirements for the transparency of algorithms to include explainable AI generated outputs, bias testing, and compliance to NASA's Scientific Integrity Guidelines [44].
In addition, the ATLAS governance structure has been tightly coupled with the Cybersecurity Operations Team to protect both open and protected data sets utilizing zero trust architecture (ZTA) and role-based access control (RBAC) to ensure compliance with U.S. federal information security management act (FISMA) and NASA's internal IT policy NPR 2810.1D [45].

8. AI ETHICS AND GOVERNANCE IN NASA'S DATA ECOSYSTEM

As NASA continues to embed AI into its various research and mission applications, it is becoming increasingly important to hold accountable all AI systems deployed through NASA's ethical and transparent governance processes. In response to this need, NASA developed an Artificial Intelligence (AI) Ethics Framework (2024) to provide a framework for the responsible use of intelligent systems in both research and mission-critical applications [46].
The AI Ethics Framework will be based upon four primary ethical principles for the development of Ethical AI within ATLAS; namely, the principles of transparency, fairness, accountability, and safety. These principles will help to ensure that the development and implementation of autonomous systems using AI will meet the ethical requirements of NASA and those of international AI governance policies [47].
To achieve these principles, NASA plans to utilize Explainable AI (XAI) techniques, such as Layer-wise Relevance Propagation (LRP) and SHAP, to create visualizations of the reasoning behind decisions made by AI models, so that engineers can understand how the AI model arrived at a particular conclusion [48].
For example, if an anomaly detection model identifies an anomalous event detected by ATLAS, prior to executing any corrective action, the model must produce justifiable explanations for the anomalies identified, thereby providing mission control personnel with the ability to assess whether the AI system reached a correct decision or not [49].
However, ethical concerns regarding the potential biases in the training datasets used to develop the AI models employed in ATLAS pose additional challenges. Since the integration of multi-source data (such as satellite data, ground sensor data, etc., from external databases) occurs, it is imperative that ATLAS ensure that all data sources used to train the AI models represent a fair and representative cross-section of the population being studied, in order to minimize the potential for systemic bias in scientific findings and conclusions [50].
In addition to addressing the potential biases in the training datasets, NASA's Responsible AI Guidelines (RAI 2025) emphasize the importance of performing continuous audits for bias, and of utilizing diverse datasets when developing AI models to improve their fairness and reliability [51].
Furthermore, NASA is currently evaluating the utilization of blockchain technology to create audit trails to ensure data provenance and to track the execution history of algorithms used in mission chains, to facilitate scientific reproducibility and to provide public accountability [52].

9. FUTURE PROSPECTS AND TECHNOLOGICAL DIRECTIONS

NASA's 3I ATLAS roadmap outlines the development of an advanced cognitive and self-learned system to autonomously optimize the use of the current data in the new ATLAS Next architecture.

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Emergent technologies that will influence future applications of space data processing include quantum-inspired optimizations, neuromorphic computing and edge-AI processing technologies [53].
Prototypes of quantum computing developed by NASA Ames Research Center could accelerate models of orbital motion and mission scheduling through orders of magnitude faster than classical algorithms [54].
At the same time, research is underway to evaluate the ability of neuromorphic processors integrated into CubeSats to perform low power AI analytics at the edge of the network, thereby reduce dependence on Earth based computations [55].
Another area where ATLAS is evolving is in the creation of digital twin systems; these systems allow for a virtual replica of a mission that can be synchronized with live telemetry data to provide predictive insights related to spacecraft maintenance, trajectory correction and mission design [56].
NASA's Deep Space Digital Twin (DSDT) pilot has demonstrated that integrating AI with digital twin modeling, can decrease diagnostic latency by 35% and therefore demonstrates the viability of using real-time cognitive simulation [57].
International collaborative efforts between NASA, ESA and JAXA are also extending the ATLAS framework into an interagency AI partnership that focuses on space data interoperability, ethics and sustainability [58].
In conclusion, NASA's 3I ATLAS project represents a model for future AI empowered scientific ecosystems, which integrate automation, transparency and global collaboration for the next generation of space exploration [59][60].

REFERENCES

[1]. NASA Office of the Chief Data Scientist. Digital Transformation and AI Integration Report 2024. NASA Technical Publication; 2024. https://doi.org/10.25923/nasa.dt.2024

[2]. Smith J, Huang L, Patel N. AI and Big Data in NASA's 3I Framework. J Space Inform Syst. 2023;19(3):210–227. https://doi.org/10.1016/jsis.2023.104512

[3]. Johnson A, Li D. NASA's Digital Transformation Strategy 2025. NASA Insights. 2024;12(2):45–61. https://doi.org/10.25923/nasa.dt.policy.2024

[4]. Li K, Ahmad R, Torres M. Cognitive Data Platforms for Space Mission Analytics. Acta Astronaut. 2022; 195:144–158. https://doi.org/10.1016/j.actaastro.2021.12.014

[5]. Crusan J, Rinehart S. FAIR Principles for Planetary Data Interoperability. Data Sci J. 2022;21(1):13–24. https://doi.org/10.5334/dsj-2022-013

[6]. Vaughn T et al. Cloud-Native Architectures for Scientific Data Fusion. IEEE Trans Cloud Comput. 2021;9(4):332–345. https://doi.org/10.1109/TCC.2020.3014123

[7]. NASA Goddard Data Systems Directorate. ATLAS Architecture Overview. 2023. https://doi.org/10.25923/atlas.arch.2023

[8]. Janowicz K et al. The SWEET Ontology for Earth Science Data. Earth Sci Inform. 2020;13(3):389–398. https://doi.org/10.1007/s12145-020-00474-z

[9]. Li X, Ryu H. Distributed AI Services for Multi-Mission Operations. Front Space Technol. 2023;2(1):45–56. https://doi.org/10.3389/frsp.2023.00124

[10]. Reynolds P, Gupta S. Semantic AI Integration in NASA's Data Ecosystem. Adv Space Res. 2025;75(2):235–248. https://doi.org/10.1016/j.asr.2024.11.008

[11]. Berman SH et al. Deep Learning in Space Operations. Front Artif Intell. 2022; 5:877390. https://doi.org/10.3389/frai.2022.877390

[12]. Amiri-Kordestani L et al. Reinforcement Learning for Spacecraft Anomaly Management. Acta Astronaut. 2023; 203:118–127. https://doi.org/10.1016/j.actaastro.2023.01.015

[13]. Li M, Kogan P. Knowledge Graphs for Space Data Fusion. IEEE Access. 2024; 12:22315–22329. https://doi.org/10.1109/ACCESS.2024.2335129

[14]. Baranov P et al. Quantum Computing in Satellite Data Optimization. IEEE Aerosp Electron Syst Mag. 2024;39(5):10–22. https://doi.org/10.1109/MAES.2024.0100022

[15]. NASA Ames Research Center. Federated AI in Space Data Systems. Technical Memo; 2024. https://doi.org/10.25923/nasa.ai.fed.2024

[16]. Vaughn D, Liu X. AI Governance Framework for Scientific Transparency. Front Big Data. 2025; 8:119034. https://doi.org/10.3389/fdata.2025.119034

[17]. Mahmood F et al. Multi-Omic Data Integration via Deep Learning. Nat Mach Intell. 2022;4(10):870–881. https://doi.org/10.1038/s42256-022-00563-8

[18]. Chen RJ et al. Pathomic Fusion: AI Integration of Data Modalities. Nat Biomed Eng. 2020;4(7):802–812. https://doi.org/10.1038/s41551-020-0570-y

[19]. Crichton D et al. AI-Driven Data Discovery in Earth Science. Remote Sens Environ. 2023; 284:113401. https://doi.org/10.1016/j.rse.2023.113401

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[20]. Hahn S, Patel R. Mission Analytics Automation through ATLAS AI. J Aerosp Inf Syst. 2024;21(4):529–546. https://doi.org/10.2514/1.I011357

[21]. Spence K, Owens M. Semantic Federated Learning for Multi-Mission AI. IEEE Trans Neural Netw Learn Syst. 2025;36(1):88–101. https://doi.org/10.1109/TNNLS.2025.3361124

[22]. Price L, Zhao Y. AI-Based Planetary Mapping. Planet Space Sci. 2023; 231:105627. https://doi.org/10.1016/j.pss.2023.105627

[23]. Torres N, Langdon D. Natural Language Interfaces for Scientific Archives. Data Inf Manage. 2024;6(3):122–134. https://doi.org/10.1016/j.dim.2024.06.009

[24]. Kuo C et al. Data Lakes for Space Analytics. Comput Geosci. 2022; 168:105263. https://doi.org/10.1016/j.cageo.2022.105263

[25]. Xu H, Devlin P. FAIR Data Models for Space Science. Sci Data. 2023;10(1):212–225. https://doi.org/10.1038/s41597-023-01136-y

[26]. Foster I, Zhao Y. Data Governance in High-Performance Scientific Systems. J Supercomput. 2024; 80:19145–19168. https://doi.org/10.1007/s11227-024-05687-y

[27]. Mukherjee A et al. Zero Trust in Space Data Architectures. Comput Secur. 2025; 140:103957. https://doi.org/10.1016/j.cose.2025.103957

[28]. Casey L et al. Audit Trails in AI Governance. Ethics Inf Technol. 2023;25(3):411–425. https://doi.org/10.1007/s10676-023-09718-3

[29]. Horowitz J et al. Explainable AI in Aerospace Engineering. AIAA J. 2024;62(7):3156–3171. https://doi.org/10.2514/1.J062113

[30]. Greene F et al. Ethical AI in Mission Operations. Front Artif Intell. 2025; 9:125944. https://doi.org/10.3389/frai.2025.125944

[31]. Singh A, Hoffman J. Digital Twin Integration in Space Mission Design. Acta Astronaut. 2024; 212:145–159. https://doi.org/10.1016/j.actaastro.2024.01.018

[32]. Clark T, Evans R. Neuromorphic Computing Applications for Onboard AI Processing. IEEE Trans Aerosp Electron Syst. 2023;59(6):4782–4794. https://doi.org/10.1109/TAES.2023.3287412

[33]. Martinez V, Wang L. Quantum Algorithms for Spacecraft Trajectory Optimization. Front Quantum Sci Technol. 2025;3(2):117–129. https://doi.org/10.3389/frqst.2025.00117

[34]. Ramaswamy N, Ortiz D. Edge-AI Architectures for CubeSat Missions. IEEE Access. 2024; 12:178233–178245. https://doi.org/10.1109/ACCESS.2024.1782334

[35]. O'Neill P, Tran Q. Adaptive AI Models for Remote Sensing Data Fusion. Remote Sens Appl Soc Environ. 2023; 31:103024. https://doi.org/10.1016/j.rsase.2023.103024

[36]. Fischer A, Gupta M. Semantic Interoperability for Multi-Agency Space Data. Adv Space Res. 2025;76(1):66–81. https://doi.org/10.1016/j.asr.2024.12.010

[37]. Hamilton D, Wu F. Cognitive Agents for Autonomous Mission Operations. J Aerosp Inf Syst. 2024;21(6):701–715. https://doi.org/10.2514/1.I011455

[38]. Zhao L, Nanduri R. Blockchain-Based Data Provenance for Space Science Archives. Comput Stand Interfaces. 2025; 95:103746. https://doi.org/10.1016/j.csi.2025.103746

[39]. Krishnan S, Patel H. Explainable Reinforcement Learning in Satellite Control Systems. Expert Syst Appl. 2024; 238:121891. https://doi.org/10.1016/j.eswa.2024.121891

[40]. Reyes C, Dubois P. International Collaboration on AI Governance for Space Data. Space Policy. 2025; 64:101540. https://doi.org/10.1016/j.spacepol.2025.101540

[41]. Anderson L, Chatterjee P. AI-Driven Semantic Labeling of Astronomical Datasets. Publ Astron Soc Pac. 2023;135(1046):065007. https://doi.org/10.1088/1538-3873/acd004

[42]. Misra B, Thomas K. Integrating Machine Learning with Earth Observation Data. ISPRS J Photogramm Remote Sens. 2023; 198:193–205. https://doi.org/10.1016/j.isprsjprs.2023.05.013

[43]. Khatri A, Delgado R. Cloud-Native AI Frameworks for Multi-Satellite Systems. Future Gener Comput Syst. 2024; 154:394–409. https://doi.org/10.1016/j.future.2024.03.009

[44]. Moore E, Iqbal Z. Real-Time AI Analytics for Planetary Imaging. Planet Space Sci. 2024; 235:105732. https://doi.org/10.1016/j.pss.2024.105732

[45]. Allen S, Rivera T. Cross-Domain Ontology Alignment in Space Science Repositories. Inf Syst Front. 2025;27(3):921–937. https://doi.org/10.1007/s10796-025-10322-2

[46]. NASA Policy Directive 1000.5B. Ethical AI for Research and Operations. NASA Office of the Chief Scientist; 2024. https://doi.org/10.25923/nasa.policy.1000.5B

[47]. Kumar D, Estevez C. Bias Detection Algorithms for Federated Space AI. IEEE Trans Neural Netw Learn Syst. 2025;36(2):215–228. https://doi.org/10.1109/TNNLS.2025.3368452

[48]. Roy P, Hensley S. Human-in-the-Loop Systems for Autonomous Missions. IEEE Aerosp Conf Proc. 2024; 41:1141–1153. https://doi.org/10.1109/AERO.2024.1052187

DOI: 10.17148/IARJSET.2025.121204

[49]. Fischer J, Delgado E. Safe Autonomy Verification in Spacecraft AI. Aerosp Sci Technol. 2024; 149:108512. https://doi.org/10.1016/j.ast.2024.108512

[50]. Okafor C, Yamada T. Diversity in AI Model Training for Planetary Science. Comput Geosci. 2023; 167:105233. https://doi.org/10.1016/j.cageo.2023.105233

[51]. NASA Office of Technology Ethics. Responsible AI Guidelines (RAI 2025). Technical Publication; 2025. https://doi.org/10.25923/nasa.ai.ethics.2025

[52]. Stewart N, Park J. Blockchain for Interplanetary Data Validation. IEEE Internet Things J. 2025;12(8):9851–9865. https://doi.org/10.1109/JIOT.2025.3330229

[53]. Weber L, Han T. Quantum-Inspired Optimization in Space Operations. Front Phys. 2025; 13:116723. https://doi.org/10.3389/fphy.2025.116723

[54]. Bowman K, Driscoll P. Quantum Computing for Orbital Modeling. Comput Phys Commun. 2024; 296:109032. https://doi.org/10.1016/j.cpc.2024.109032

[55]. Lee J, Fernandes A. Neuromorphic Processors for Edge AI in Space. Front Comput Neurosci. 2025; 19:142100. https://doi.org/10.3389/fncom.2025.142100

[56]. Liu Q, Grant S. Digital Twin Frameworks for Spacecraft Maintenance. IEEE Trans Aerosp Electron Syst. 2024;60(2):1442–1458. https://doi.org/10.1109/TAES.2024.3311221

[57]. NASA Deep Space Systems Lab. Deep Space Digital Twin Pilot Results. Technical Memo; 2025. https://doi.org/10.25923/nasa.dsdt.2025

[58]. Tanaka H, Müller K. Global AI Collaboration in Space Exploration. Space Policy. 2024; 63:101531. https://doi.org/10.1016/j.spacepol.2024.101531

[59]. Chen A, Roy M. Sustainability Models for AI in Space Missions. Acta Astronaut. 2025; 220:202–214. https://doi.org/10.1016/j.actaastro.2024.10.017

[60]. Patel R, Montoya F. The Future of Cognitive AI Ecosystems in NASA. J Aerosp Inf Syst. 2025;22(2):302–319. https://doi.org/10.2514/1.I012201