Supplementary Table S1: Summary of gut microbial alteration during spaceflight

Microbiome	species	Associated conditions	Changes
Gut	Akkermansia[1, 2]	Increase in the inflammatory immune response	↓
Gut	*Fusicatenibacter*[1]	Increase in the inflammatory immune response	↓
Gut	*Pseudobutyvibrio*[1]	Increase in the inflammatory immune response	↓
Gut	*Parasutterella*[2]	Chronic intestinal inflammation in patients with inflammatory bowel disease (IBD)	↑
Gut	*Bifidobacteria* [3-5]	Immune system injury	↓
Gut	*Lactobacilli*[3]	Immune system injury	↓
Gut	*Bacteroides*[3]	Opportunistic pathogen	↑
Gut	*Salmonella*[6]	Increased virulence and antibiotic resistance (in-vitro)	
Gut	*Escherichia coli*[6]	Increased virulence and antibiotic resistance (in-vitro)	
Gut	*Clostridiaceae*[7]	Increase in the inflammatory immune response	↓
Gut	Firmicutes to Bacteroidetes (F/B) ratio[8]	Ratio changes noted in response to spaceflight, however ratio returned to preflight levels within weeks of landing	↑
Gut	*Faecalibacterium prausnitzii,*[2]	Decreased production of some short-chain fatty acids (SCFA)	↓
Gut	*Parasutterella*[1]	Chronic intestinal inflammation in patients with inflammatory bowel disease (IBD)	↑
Skin	Proteobacteria (mostly Gamma and Betaproteobacteria)[1]	Inversely associated with inflammation and allergy sensitization	↓
Skin	Firmicutes[1]		↑
Skin	*Staphylococcus aureus*[1, 9-11]	Spaceflight-isolated *staphylococcus* species were resistant to at least 1 antibiotic	↑
Skin	*Streptococcal*		↑
Skin	*Pseudomonas*[9, 10]		↑
Skin	Enterobacteriaceae[9]		↑
Nasopharynx	*Staphylococcus*[1, 12]	Prevalence of *staphylococcus aureus* may be associated with chronic rhinosinusitis, allergic rhinitis, nasal polyps, and asthma	↑
Nasopharynx	*Corynebacterium*		↑
Nasopharynx	*Bifidobacterium*[1, 13]	May have a protective effect on allergic rhinitis	↑

Supplementary Table S2: Summary of immune/cytokine changes during spaceflight

Immune/cytokines	Inflight (long duration) (at least 6 months)	Post spaceflight (after returning to Earth)
CXCL8[1]	↑	
IL-8[1, 14]	↑	
IL-1b[1]	↑	
IL-1ra[1, 14]	↑	
TNFa[1, 15]	↑	
IL-6[15, 16]		↑
IL-3[17]	↑	
IL-7[17]	↑	
IL-15[17]	↑	
IL-12p40[17]	↑	
TGF-ß1 and TGF-ß2[17]	↑	
IL-10[15, 16]		↑
IL-1ra[15, 16]		↑
CCL2[15, 16]		↑
CRP[15, 16]		↑
Saliva GM-CSF[17]		↓
Saliva IL-12p70[17]		↓
Saliva IL-10 [17]		↓
Saliva IL-13[17]		↓

Supplementary Table S3: Summary of diet recommendation during spaceflight

Diet and Supplements	
Protein intake, % of kcal	12–15% of total daily energy intake
Carbohydrate intake, % of kcal	50% to 55% of total daily energy intake
Fat intake, % of kcal	30–35% of total daily energy intake
Water	> 2 liters per day
Total dietary fiber, g/d	10–25 grams per day
Fruits and vegetables	Recommended

Vitamin D supplements	Recommended

Supplements of A, B6, B12, C, E, K, Biotin, Folic acid are not recommended at this time due to insufficient evidence[18, 19]

Supplementary Table S4: Summary of AI technology and potential applications in space

Problem	Technology	Potential applications
Imaging	The Space-Feasibility Body Composition and Body Shape Analysis for Long Duration Missions (ASTRO3DO) project[20]	3D optical scanners using AI to monitor an astronaut's total body compositions (lean, fat, percent fat, BMD), regional compositions (visceral fat, subcutaneous fat, lumbar spine BMD)
Imaging	AMO project[20, 21] AMO MDSS computer system	Virtual medical officer (Tietronix Intelligent Medical Crew Assistant), Augmented Reality enhanced ultrasound improves the reliability of ultrasound image interpretations
Imaging	AI-enhanced ultrasound[22]	AI-enhanced clinical-grade images for inflight echocardiography (UltraSight with GE Healthcare) and point of care ultrasound (GE Healthcare Vsan Air wireless transducer)
Imaging	Deep learning enhanced microtomography[23]	CMCT system has great promise for temporal bone imaging
Monitoring	Random forest Bayes network algorithm[24]	AI could monitor or predict colorectal cancer based on analysis of fecal and gut microbiota
Monitoring	MitoMo (Proprietary algorithm)[25]	AI could monitor microscopic changes in mitochondria
Monitoring	DeepMAge (Deep learning)[26]	AI could monitor microscopic changes in epigenetics
Monitoring	XGBoost[27-29]	AI could monitor small changes in telomere-length dynamics
Monitoring and prediction	Pro-inflammatory cell phenotypes and plasma cytokines[30, 31]	AI could monitor microscopic changes in levels of inflammatory cytokines
Monitoring and prediction	Proprietary ML algorithm[32, 33]	AI could monitor intracranial pressure levels using ultrasonography of the optic nerve sheath diameter in order to predict SANS development
Biosensors	Generative AI[34] Wearable technology[35]	Synthetic Astroskin Data (detect electrocardiographic changes)
Prediction	CRISP 2.0 model Intel's Open Federated Learning (OpenFL) framework[36, 37]	AI could predict the genes or novel biomarkers for the development of cancer secondary to radiation exposure based on data from a

		combination of mouse, human, and genetic studies
Unknown or novel risk factors prediction	CRISP[37, 38] Gradient boosting decision trees[39] Logistic regression[40]	AI could identify 'hidden' risk factors from simulated microgravity and radiation exposure
Prediction	Proprietary ML algorithm[41]	AI could detect the risk of cerebrovascular disease using estimates of carotid-femoral pulse wave velocity values obtained from doppler ultrasound
Prediction	Hybrid method (deep learning and empirical mode decomposition)[42]	AI could potentially predict radiation dose estimations
Prediction	Support Vector Machines[43]	AI potentially predict genomic signatures of human radiation response
Device, organ	AI-enhanced 3D printing[44, 45]	In a microgravity environment, 3D-printed soft tissues will maintain their shape.
Medical Decision Support System	Autonomous Medical Operations (AMO)[20]	AI-assistance to aid astronauts in the timely diagnosis (e.g., ultrasound) and treatment of emergent conditions (e.g., advisory software, virtual assistance)
Triage	Operations (AMO)[20]	AI assistant that assigns degrees of urgency to a medical scenario
Biosensors	Wearable devices, motion sensors[35]	A combination of AI and wearable technology could monitor vital signs, sleep cycle
Interpretation	K-Means clusters and Support Vector Machine[46]	AI could potentially provide a complementary approach to classic statistical analysis and enable a more robust assessment of microstructures (e.g., bone microarchitecture) using microCT

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