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# FEDERATED LEARNING FOR SPACE MEDICINE RESEARCH AND ITS APPLICATION FOR SPACEFLIGHT ASSOCIATED NEURO-OCULAR SYNDROME (SANS)

**Abstract**

Small study populations (N), small numbers of study subjects (n), and small datasets have long been constraints in researching the physiological changes that occur during human spaceflight. Additionally, cross-agency sharing of crew medical data creates privacy risks, as anonymity is less certain with small numbers of study subjects and small datasets. These risks may limit the possibility for multi-agency space medicine consortia to share data and achieve the number of study subjects and dataset sizes needed to achieve statistical significance in addressing space medicine problems. This limitation is particularly challenging for artificial intelligence (AI) applications, which could provide the increased onboard medical autonomy needed during human spaceflight exploration missions, but are difficult to train on the small datasets characteristic of space medicine. To address these challenges, we describe a method that uses an emerging machine learning paradigm called federated learning (FL). FL enables the training of AI models on decentralized datasets, rather than centralized datasets, as is required with traditional machine learning paradigms. After decentralized training on local data at each site, the local model parameters are shared and aggregated into a cross-agency global model. This method serves to increase the number of study subjects, dataset size, and accuracy of AI models without raw data sharing. Additionally, medical privacy and security risks characteristic of traditional machine learning paradigms are avoided, and local energy consumption, data transfer, and communication costs may be reduced. Moreover, the number of study subjects and dataset size are increased to maximize use of the full study population enabled by multi-agency consortia. These FL capabilities may be applied to enable advancement in AI models to identify, monitor, and prevent Spaceflight Associated Neuro-ocular Syndrome (SANS), which affects

nearly two thirds of crew members on long-duration spaceflight missions. Altogether, FL can serve as a useful tool to fill exploration class mission gaps for SANS, enable autonomous medical operations, and improve space medicine and crew performance during spaceflight across space agencies to reduce risks for future long-duration missions to the Moon and Mars.