**HARNESSING ARTIFICIAL INTELLIGENCE FOR MEDICAL DIAGNOSIS AND TREATMENT DURING SPACE EXPLORATION MISSIONS**

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**A. INTRODUCTION**

Tremendous media attention accompanied the public launch of generative artificial intelligence (AI) models[1], and novel applications of these technologies have continued to evolve. Advancements in AI have long been predicted to influence numerous private and public sectors, including medicine[2], and the field of aerospace medicine stands to benefit tremendously from AI integration. Many use cases for AI precede the introduction of the generative AI models[3], but the supportive potential of these tools in healthcare has not yet been fully realized. To date, AI is most commonly implemented to support terrestrial medical care through risk prediction in hospital electronic health records (EHRs), automated continuous waveform analysis, and radiological and histopathological imaging analysis[4] with an increasing number of products achieving FDA-approval[5]. However, myriad applications of AI are described in the literature but are not yet accessible to clinicians. These have tremendous opportunity to be leveraged for clinician support in the austere environment of spaceflight, but a categorical understanding of the technology available and its projected evolution is critical for implementation. While AI cannot fully replace clinicians or chief medical officers (CMOs) of exploration class space missions in the foreseeable future, one of the most exciting opportunities lies in the genesis of a physician-curated 'supervised AI' clinical decision support system (CDSS). CDSS can facilitate clinical care by processing inputs and making diagnostic suggestions for further work-up or expanding a differential diagnosis. They may further provide treatment recommendations using precision-medicine algorithms, including those in emergency and atypical clinical scenarios. Given the 40-minute round trip communication delay between Mars and ground support, space medicine as a field must evolve to increasingly incorporate CDSS and AI technologies for support of human health and performance in the pursuit of Earth-independent medical care.

Several AI architectures have been adopted or are being researched for use in medical care, including but not limited to machine learning (ML) algorithms[6], convolutional neural networks (CNNs)[7], recurrent neural networks (RNNs)[8, 9, 10], artificial neural networks (ANNs or NNs)[11, 12], generative adversarial networks (GANs)[13], natural language processing (NLP) models[14, 15], transformers[16], and large language models (LLMs)[17] (**Table 1**). Considering that foundation of today's generative pre-trained transformer models, known as "selective attention", was first described in 2017[18], the pace of innovation in this area of software engineering is astonishingly rapid. The ability of AI technologies to improve both diagnostics and therapeutics within medicine will undoubtedly continue to advance at a similarly breakneck speed[19]. However, it is essential to evaluate the real-world performance of these tools and consider both ethical and legal ramifications of their use prior to mass implementation for patient care[20, 21]. Even when approved, the technology may not necessarily be readily adopted by physicians in practice[22]. However, with increasing clinical demands on medical professionals, especially in the wake of the COVID-19 pandemic[23, 24], openness to thoughtful AI implementation in clinical practice is increasing[25]. Clinicians that are earlier in their training are less reticent to adopt these technologies, however, given the recency of generative language model (GLM) proliferation and lack of validation, this is not yet addressed in most formal medical education curricula[26]. Space medicine affords a unique opportunity for CDSS and AI to be developed and validated with the security of a terrestrial support system as a contingency plan for the safety and health of astronauts.

As our species embarks on long duration exploration missions (LDEMs), the complexity of medical care will expand beyond the care required for previous orbital missions to the International Space Station (ISS)[27]. When considering the physiological adaptations that will occur during these missions[28], maintenance of crew health by the designated CMO will require significant support. Further, resources will be limited, rapid re-supply will not be feasible, and ground support will be more limited by distance leading to both communication delays[29] and impaired timely transmission of large data files (e.g., dynamic ultrasound images). These factors make Earth-independent medical operations (EIMO) aboard the spacecraft essential to mission success. Therefore, these missions will benefit from an immediately available, multidisciplinary CDSS to assist CMOs or other crewmembers in the diagnoses, treatment, and management of medical conditions[30]. Frameworks for these tools have been suggested[31, 32], with most noting the advantages of AI to assist with medical decision-making and prompt delivery of medical care[33, 34]. Others have suggested the use of AI both pre- and post-flight to maximally mitigate in-flight risk[35]. Currently, just-in-time training (JITT) for NASA CMOs does not incorporate training in a CDSS, in part because this tool has not been targeted to spaceflight concerns or integrated into the medical system. Ultimately, development of an all-purpose CDSS will require consideration of mission goals, mission segments (i.e., launch, spaceflight extravehicular activities [EVAs], Lunar landing, etc.), associated medical risks, and the logistical software and hardware constraints.

Informing Mission Planning via Analysis of Complex Tradespaces (IMPACT) is a probabilistic risk assessment (PRA) and trade space model developed by the NASA Exploration Medical Capability (ExMC) Element. As an evolution of the previous Integrated Medical Model (IMM)[36, 37], this mission planning tool can propose a medical system (with adjustable mass and volume thresholds), hypothesize which medical conditions are most likely to occur for a given design reference mission (DRM), and provide risk assessments for outcome metrics such as loss of crew life (LOCL), need for return to definitive care (RTDC), and crew task time lost (TTL). IMPACT, at present, contains 119 prioritized medical conditions that may arise in spaceflight in its evidence library[38]. These preliminary conditions were selected based on either their frequency or acuity in spaceflight, and physician subject matter expert (SME)-led teams performed exhaustive literature searches to compile the most robust and relevant incidence data available for populating the model. In addition to incidence, further data was used to drive a best- vs. worst-case probability, the risk of LOCL, RTDC, and TTL, and the diagnostic and therapeutic resourcing, knowledge, skills, and abilities required for management of every condition.

To test the first version of IMPACT, the ExMC Clinical and Science Team (CST) introduced an extended duration late-Artemis design reference mission (DRM)[39] totally nine months and six-days in length. This DRM captures three days transit to Lunar orbit, three months on the Gateway space station, three months on the Lunar surface with both time in habitat and 36 extravehicular activities (EVAs), a subsequent three months on Gateway, and three days travel in return to Earth. The four-member (two male and two female) crew modeled are representative of the NASA astronaut population with no pre-existing medical conditions. One hundred thousand Monte Carlo simulated missions were run to characterize a proposed medical system for optimal medical risk mitigation for this DRM[40]. The conditions most likely to arise and the notional outcome metrics from these example datasets are shown in **Figure 1**[41, 42, 43].

As NASA continues to iterate and update the IMPACT model, the purpose of this review is to survey existing AI tools that could potentially assist a future CMO with the diagnosis and management of the medical conditions identified by IMPACT during this late-Artemis DRM. Given that space exploration missions will not have the luxury of rapid communication with terrestrially based medical specialists, CDSS will be increasingly necessary to support Earth-independent, near-autonomous medical care in spaceflight. However, to forecast the use of AI and CDSS in future lunar and Martian exploration missions, we must first determine the current capability of AI frameworks to improve crew health and performance statistics. This comprehensive review serves to explore whether the current state of AI can be leveraged to facilitate creation of the CDSS that will inevitably be required to support astronaut crew.

## B. METHODS

Using PubMed and Google Scholar, we performed a literature survey of those AI tools applicable to the prediction, triage, diagnosis, and management of the medical conditions highlighted by IMPACT. The search included the following keywords and phrases: “Chatbot” “Healthcare” “Diagnosis”, “Artificial intelligence” “natural language processing” “medicine” “ChatGPT”, "large language model" "healthcare" "diagnosis", "generative" "ai" "healthcare" "diagnosis" "chat", “Artificial intelligence” “natural language processing” “medicine” "differential diagnosis", “natural language processing” "differential diagnosis", "explainable" "artificial intelligence" "differential diagnosis" "medicine", "Natural language processing" "diagnosis" "[medical condition]", "natural language processing" "chatbot" "[medical condition]", “Artificial intelligence” “diagnosis” “[medical condition]”, and “Artificial intelligence” “[medical condition]”. Each [medical condition] and additional keyword/phrases included within the reference search are outlined in **Figure 1**. Included articles were published between the January 2017 and May 2023, as the sentinel paper discussing “selective attention” inherent to generative pre-trained transformer models titled “Attention Is All You Need” was published in June 2017[18]. Where applicable, we reviewed the top 1000 research articles (based on relevance) for each of the keywords/phrases. For exclusion criteria, we omitted tools with training sets exclusive to images or text from a pediatric patient population. We also excluded any medical diagnostic tools (CT, MRI) or procedures (endoscopy, surgery) likely unavailable due to size and systems constraints, CMO skillset, and/or inherent procedural risks. This reference search yielded over 100,000 original articles and reviews. After primary assessment of titles and abstracts, 929 original research articles were deemed pertinent. A secondary full review of those manuscripts and removal of duplicates identified 567 original research articles and reviews. After final assessment, including the removal of articles not relevant to the space exploration and the addition of original research manuscripts uncovered within review articles, 455 original research articles (and associated reviews) were included in this literature survey (**Figure 2**).

## C. AI TOOLS FOR SPACE EXPLORATION

Our survey highlighted several AI tools for the triage, diagnosis, and management of those medical conditions highlighted for the proposed DRM including: Lunar Dust Exposure (20), Insomnia (33), Suit Contact Injury (24), Paresthesia (6), Headache (25), Ear/Sinus Barotrauma (67), Skin Rash/Abrasion (75), Eye Irritation/Corneal Abrasion/Ulcer (53), Shoulder Injury/UE Sprain (65), LE Sprain (25), Back Sprain (20), Neck Sprain (28), Acute Diarrhea (12), Wrist Fracture (35), Decompression Sickness (5), Chemical Eye Burn (1), Bacterial Skin and Soft Tissue Infection (60), Respiratory Failure (50), Urinary Tract Infection (42), Trauma-Related Hypovolemic Shock (45), Abnormal Uterine Bleeding (28), Ebullism (4), Obstructed Airway (25), Toxic Inhalation of Combustion Products (1), and Dental Abscess (44), with the number of pre-screened articles for each medical condition indicated within parenthesis. These AI tools were then rescreened and grouped within ten systems-based categories including general diagnostic tools, tools to diagnose and manage respiratory, dermatologic, neurologic, auditory and vestibular, ophthalmic, musculoskeletal, infection-associated, and gynecologic conditions, as well as tools that could be deployed in the setting of trauma and emergency situations (**Figure 3**).

### 1. GENERAL DIAGNOSTIC TOOLS

The foundation of a next-generation spaceflight CDSS will be an agent capable of producing a real time differential diagnosis while conversing with CMOs or crewmembers and guiding them through nuanced relevant information retrieval of the patient’s symptoms and medical history. This CDSS would then also suggest the most appropriate diagnostic work-up for helping the CMO arrive at a likely diagnosis before implementing care. The system would be able to receive numerous data inputs, including but not limited to text, voice, visual images (camera or X-ray), video (camera or ultrasound) as well as biometric (sensors), continuous monitoring [LifePak (Stryker, Kalamazoo, Michigan) or other basic vital sign device], and laboratory diagnostic data collected onboard the spacecraft. AI-based general diagnostic systems for the identification and management of numerous diseases are explored in this survey (**Table 2**). We open by discussing many of the foundational AI tools developed.

The earliest AI tool identified dates to 2017, when Ni et al. developed a chatbot known as Mandy for automated patient interviews using NLP alongside knowledge-driven diagnostics. Using a diagnostic module, symptom-to-cause mapping, and question generator to facilitate patient interview, Mandy can help diagnose over 1000 diseases. To improve diagnostic accuracy, the authors proposed the integration of reinforcement and case-based incremental learning algorithms[44]. Later, a study evaluating the IBM Watson NLP and alternative decision tree ML model for problem list generation was performed. Here, physicians completed 27 assessments and compared their own problem lists to those generated by IBM Watson. While physicians preferred their own problem lists, Watson was able to detect at least one missed problem in 90% of cases[45].

In 2018, Quro was developed for patient triage and initial symptom assessment using NLP and medical entity detection. When triaging based on urgency, Quro accurately assessed those symptoms in 25 of 30 cases for an overall accuracy of 83.3%[46]. Additionally, deep reinforcement learning through the REFUEL algorithm, consisting of both reward shaping and feature rebuilding techniques, was proposed to increase diagnostic accuracy of reinforcement learning models. While these models already outperform tree-based methods for large disease datasets, the large search and small feature space increased time-to-diagnosis. Through the identification of key symptoms, REFUEL achieved a top-5 differential diagnosis accuracy of 91.71% amongst 73 diseases and 75.04% amongst 255 diseases[47]. Furthermore, Greg, ML is a ML model for disease diagnosis consisting of a natural language module and diagnostic suggestion module using the DAIMO instance labeler. Preliminary investigation using over 22,000 medical records for approximately 50 diseases reported promising diagnostic accuracy results with an F1-score (indicative of predictive performance) over 95% for each diagnosis[48]. More recently, the dataset was expanded to over 700,000 records and 1712 differential diagnoses[49].

Furthermore, Wei et al. designed a dialogue system consisting of natural language understanding, a dialogue manager, and natural language generation modules for symptom detection, extraction, and disease diagnosis using a deep Q-network, which combines deep neural networks and reinforcement learning to allow systems to function in complex environments. The model outperformed both random and rule-based support vector machines (SVMs), which are early models of supervised learning, for diagnostic accuracy[50]. More recently, the group implemented a two-level hierarchy into the dialogue policy learning module. Here, a master is responsible for triggering a lower-level worker (based on the symptom set) which then feeds into a disease classifier consisting of a two-layer Multi-Layered Perceptron (MLP) framework for more accurate disease diagnosis. Further expansion of the disease dataset is required, however, for the generation of a more robust general diagnostic agent[51].

In 2019, Tootooni et al. also developed CCMapper, a chief complaint symptom mapping tool, using NLP of free-text chief complaint data. When compared to symptom mapping and chief complaint categorization by two board-certified physicians, CCMapper achieved a high level of agreement ($\kappa = 0.958$). The system also achieved robust predictive accuracy when mapping multiple chief complaints (F1-score of 82.3%)[52]. An automated history-taking device known as DIAANA AMHTD was developed for the diagnosis and management of 126 medical conditions using 269 curated multiple-choice questions and artificial reasoning. A randomized trial where the report generated by the DIAANNA AMHTD was or was not analyzed by a resident physician prior to differential diagnosis list generation was conducted. Results suggested that prior review of the generated list increased the percentage of correct differential diagnoses (75% vs 59%)[53]. Furthermore, Mathew et al. developed an Android application for assistive diagnosis of medical conditions using NLP of user inputs for convergence on a pre-trained dataset using k-nearest neighbors (KNN) ML[54]. These are systems that could help a CMO more accurately generate robust differential diagnostic lists, and as they only require the compute of a mobile phone, are feasible for use aboard spacecraft.

Xie et al. next proposed an expandable EHR-based knowledge network (MKN) for more accurate clinical diagnosis using both external knowledge (medical website *Yimaitong*) and text mining of the available EHR. In comparison to four ML models, the expandable MKN outperformed with a recall, precision, and F1-score of 0.719, 0.837, and 0.774, respectively. The expandable MKN was equipped with a vastly increased knowledge (1753), symptom (645), and disease (258) database for this improved performance[55]. Furthermore, a generalized adversarial regularized mutual information policy gradient (GAMP)-based dialogue system was deployed to improve patient-physician dialogue analysis. In comparison to other models, the GAMP outperformed on both overall accuracy and speed, requiring fewer interactions with the user for accurate diagnosis[56]. Future systems that can mimic physician-patient dialogue during history gathering with the affected astronaut would improve both user satisfaction and confidence in AI-generated responses. Relatedly, the commercially available Babylon Triage and Diagnostic System (Babylon Health, London, United Kingdom), which can provide both triage recommendations and differential diagnoses using Bayesian Networks, was compared to recommendations from general practitioners for 100 clinical vignettes. The Babylon system achieved a recall (80.0%) comparable to the doctor average (83.9%) while outperforming in both average precision (44.4% vs 43.6%) and F1-score (57.1% versus 57.0%) for differential diagnosis generation. When assessing triage recommendations, the Babylon system provided a safer recommendation than doctors with similar urgency appropriateness[57]. Accurately triaging care aboard spacecraft, particularly in an event requiring clinical intervention for numerous crewmembers, will be critical for medical resource distribution during LDEMs.

In 2022, a self-diagnosis agent known as Avey, consisting of a diagnostic algorithm, recommendation algorithm, and ranking mechanism powered by Bayesian models, was developed. Avey was tested on 400 clinical vignettes covering numerous body systems. Avey outperformed other symptom checkers while performing similarly to 3 board-certified physicians on 7 standard statistical measurements for differential diagnosis list accuracy[58]. Karup and Shetty also proposed a chatbot for primary healthcare diagnosis using patient reported symptoms through NLP, NNs, and decision tree classifiers, however, limited performance data was reported[59]. Additionally, the INTEGRA differential diagnosis system consisting of a web-based interface, multiple diagnosis sub-systems, and knowledge base was developed. In a preliminary evaluation, INTEGRA achieved a 60% diagnostic accuracy rate when combining two sub-systems for integrated diagnostic decision making[60].

Later, a virtual assistant known as Associated Guide Symptom Investigation and Diagnosis Assistant (A-SIDA) was developed for disease diagnosis using patient reported symptoms. Through diagnosis policy learning, association and relevance modules, and an internal critic for reinforcement learning, the model achieved overall better diagnostic accuracy while reporting an increase in user-satisfaction due to enhanced symptom investigation[61]. Furthermore, an AI-based diagnostic and clinical recommendation system known as DocOnTap was developed using data from the Ada (Berlin, Germany) Health Care Website and Infermedica (Wroclaw, Poland) API followed by word2vec disease vector construction and ML. When comparing various models, the random forest (RF) model achieved a robust accuracy of 87.23% in early validation testing[62]. Rustam et al. also proposed an automated diagnosis system powered by both pre-training of ML algorithms on disease databases and active Google (Mountain View, CA, USA) speech recognition algorithms for direct patient voice descriptions of their illness[63], highlighting how future CDSSs could interpret auditory, visual, and text-based inputs during these missions. Further, Sridhar et al. developed a self-assessment ML algorithm capable of predicting a differential diagnosis list from patient-reported symptoms utilizing SVM, RF, naive bayes, ANNs, among other classifiers with a Bagging technique. The group outperformed other ML-based models achieving a diagnostic accuracy of over 98% for 40 diseases[64], which is an attractive performance for assistive diagnosis for spaceflight crew.

With the recent shift towards LLMs, Hirosawa et al. examined ChatGPT-3 (OpenAI, San Francisco, CA, USA) as a tool for differential diagnosis list generation by prompting with clinical vignettes consisting of an associated clinical case, determined five differential diagnoses and correct diagnosis for ten common chief complaints. Physicians outperformed ChatGPT-3 for correct diagnosis overall (93.3% versus 53.3%) and for correct diagnosis inclusion within a top-5 differential diagnosis list (98.3% versus 83.3%)[65]. These data triggered researchers to use generative transformer models specifically pre-trained on large medical databases to improve model performance. In this regard, Almanac, a large-language model (LLM) for treatment recommendations and care guidelines, was evaluated by board-certified physicians on over 100 clinical scenarios. Almanac reported an 18% increase in factuality alongside safer overall recommendations when compared to ChatGPT[66].

Additionally, a specialized LLM for delivery of medical advice based on meta-AI (LlaMA, Meta, Menlo Park, CA, USA) and known as ChatDoctor was created through training on over 100,000 patient-physician dialogues. ChatDoctor includes a self-directed information retrieval system capable of using both real-time online and offline medical databases. In comparison to ChatGPT, ChatDoctor achieved a more robust precision with similar recall and F1 score. Further development will require more robust reinforcement learning for delivery of accurate responses while preventing unwanted LLM “hallucinations''[67]. Finally, the Clinical Decision Support System based on Learning-to-Rank (LTR) algorithm was developed by Miyachi et al. through analysis of physician-inputted patient symptoms, physical exam findings, lab results, and imaging test results for generation of a ranked differential diagnosis list. In preliminary testing, the approximate normalized discounted cumulative gain approach for learning-to-rank modeling outperformed the previously deployed mean squared error loss function approach when analyzing 26,000 cases[68].

Overall, the current state of general diagnostic AI tools suggests they may be able to assist with spaceflight CDDS to help improve astronaut safety and mission success for future deep space exploration missions. Any future CDSS that is deployed will have to consider numerous limiting hardware and computational factors and may only include tailored knowledge bases (such as Almanac[66] or ChatDoctor[67]) for the medical conditions predicted to occur. However, a robust CDSS capable of diagnosing a wide range of medical conditions would ideally be developed for all missions and their segments.

**2. RESPIRATORY**

Several respiratory disorders were predicted to be most frequent (lunar dust exposure[69, 70]) or cause LOCL (respiratory failure[71], ebullism[72], obstructed airway[73], toxic inhalation of combustion products[74, 75]) for the previously outlined DRM. Of utmost importance, respiratory failure is associated with several pathologies including acute respiratory distress syndrome (ARDS) and pneumothorax, among others[76]. Advanced airway management in microgravity, as needed in the event of acute respiratory failure onboard the spacecraft, is a well-researched topic due to the difficulty of intubation in this setting[77]. While microgravity poses physiological challenges to normal lung function, EVAs provide further complication due to lower pressure exposures in modern day spacesuits. Current de-nitrogenation (i.e. pre-oxygenation) protocols deployed on the ISS, however, have proven effective in preventing EVA-related lung injury[78]. Additionally, development of Lunar lung disease following toxic celestial dust exposure concerns researchers for LDEMs on the Moon or Mars surface[79, 80]. Fortunately, while protocols for adequate airway management during spaceflight have been developed[81, 82], major airway complications have not been observed in human spaceflight to date. This survey ultimately highlights relevant respiratory AI applications that could be deployed during future space exploration missions (**Table 3**). Unsurprisingly, tools addressing the major concerns of NASA HRP professionals including both Lunar dust exposure and toxic inhalation were not uncovered in this literature survey but will undoubtedly be the subject of future directed investigation.

### *2.1 Speech, Lung, and Cough Sounds*

Analysis of recorded speech patterns may allow for continuous assessment of lung function during these missions. Models such as SpeechSpiro have been developed to analyze speech patterns for lung functional parameter prediction using 60 second audio recordings[83]. Lung functional parameter data acquired by an application like SpeechSpiro could be coupled with respiratory disorder prediction models for improved diagnostic accuracy[84]. AI has also been deployed to improve classification accuracy and assessment of respiratory sounds[85, 86, 87]. Lung sound anomaly detection methods have shown preclinical success[88, 89], with the advent of digital stethoscopes and wearable technologies making point of care collection and analysis of lung sounds possible[90]. Additionally, over 48 AI tools analyzing cough sounds for the diagnosis of respiratory disorders have been developed[91, 92]. Of note, the app Healthmode performs continual cough collection through a smartphone's internal microphone using CNNs[93]. Apps of this type will lead to larger cough recording datasets for training of future AI-based applications. Ultimately, speech, lung, and cough sounds coupled with AI could assist CMO in respiratory disease recognition and diagnosis during space exploration missions.

### *2.2 Acute Respiratory Distress Syndrome (ARDS)*

Several AI tools have been developed to predict risk of ARDS development. These include models which utilize NLP of medical notes[94], an RF ML model using admission-detected clinical variables[95], and a logistic regression (LR) model using EMR features from patients with moderate hypoxia[96]. ML models which combine clinical variables with radiographic reports for ARDS detection at onset, 12-, 24-, and 48- hours in advance have also been developed[97]. Models which rely upon real-time continuous waveform data combined with both EMR and mechanical ventilator derived features[98], while robust, have limited application in space flight. NN[99] and ML[100] models which rely upon clinical laboratory data measures for superior area under receiver operator characteristic (AUROC) also have limited relevance as it is unlikely that the tools and resources required to perform these diagnostic tests would be available during LDEMs. However, models such as FAST-PACE, which utilizes only basic vital signs (blood pressure, respiratory rate, $SpO_2$, body temperature) combined with recent surgical history and health status to predict the onset of respiratory failure 6-hours before occurrence with an AUC of 0.869[101] would be helpful assistive technologies. Numerous AI applications have been developed to discriminate ARDS development from disorders of similar presentation[102, 103] or predict ARDS mortality[104, 105]. In summary, several AI tools for ARDS prediction, detection, and diagnosis have been explored but require further validation. Models with limited reliance on extensive laboratory data will be of utmost interest for LDEM CDSS.

### *2.3 Chest Radiographs*

Chest X-ray is a traditional terrestrial diagnostic tool for respiratory disorders and is an essential medical capability currently awaiting operational validation on the ISS. Though the handheld X-ray is unlikely to be included in LDEMs given mass/volume limitations, with extensive chest radiograph databases available to the public, numerous models for respiratory disease diagnosis have been developed. These applications range from models which can stratify chest radiographs into normal and abnormal classifications[106] to those capable of diagnosing ARDS[107, 108, 109] or pneumothorax with robust[110, 111, 112] or limited[113] validation testing. Hybrid deep-learning frameworks have also been developed to improve analysis of chest radiographs captured in abnormal orientations[114]. Deep learning models such as DeepMRD, developed using large-scale datasets, have achieved robust AUCs of 0.841 for abnormality detection and 0.866 for major respiratory disease diagnosis[115]. Alternatively, zero-shot chest X-ray diagnosis tools such as Xplainer have outperformed previously reported zero-shot methods[116, 117] when combined with informative user prompts[118]. While Xplainer does not require large amounts of annotated data for function, descriptive input from a board-certified physician may not be a reality during space flight. Overall, assistive analysis of chest X-rays captured by hand-held radiographic instruments may prove useful during deep space exploration missions. Efforts to curate extensive chest X-ray datasets of images captured by these instruments, while not necessary, may help improve the fidelity of deployed AI frameworks in this setting.

*2.4 Point-of-Care Ultrasound for Respiratory Diagnoses*

Bedside ultrasound will invariably be the mainstay for pulmonary imaging during LDEMs[119]. While the recently published literature within the field has focused attention to COVID-19 diagnosis[120], progress has been made for the assistive diagnosis of pneumothorax[121]. Importantly, the AI software Auto B-Lines (GE Healthcare, Chicago, IL, USA) has also been extensively tested for the assistive detection of pulmonary edema in a clinical setting[122]. Overall, numerous AI tools for the assistive diagnosis of respiratory disorders using lung function tests, chest radiographs, and point-of-care ultrasound were surveyed. While recent literature has focused extensively on COVID-19 detection and management, the pandemic only accelerated the need for AI tools for respiratory care. This measurable progress will ultimately result in deployment of numerous assistive diagnostic models in clinical practices of the future and will certainly be able to assist with diagnoses of pneumothorax, pleural effusion, and pneumonia.

**3. DERMATOLOGIC**

Dermatologic manifestations are considered the most common medical conditions observed during human spaceflight[123]. The NASA evidence library has highlighted contact dermatitis, atopic dermatitis, psoriasis, acne, allergic reactions, viral reactivations, dry skin, as well as the development of eczematous lesions as observed manifestations both in- and post-flight[124, 125]. Researchers have suggested numerous intrinsic (skin physiological changes, lack of epidermal turn over) and extrinsic (confinement, microbial exchange with habitat, limited hygiene) causative factors driving these manifestations[126]. Considering that these conditions are experienced by greater than 25-fold the general population, and account for nearly 40% of all clinical findings onboard the spacecraft[127, 128], numerous dermatologic disorders were predicted to be most frequent (EVA-related suit contact injury, spaceflight-associated skin rash, skin abrasion) or negatively impact task time (spaceflight-associated skin rash, EVA-related suit contact injury) during the proposed DRM. AI tools developed to help dermatologists assess similar clinical manifestations on Earth are surveyed here (**Table 4**).

*3.1 Suit Contact or Pressure Injuries*

Considering that astronaut suit contact injuries are not commonplace in terrestrial medicine, there are no documented examples of AI tools specifically developed for their prediction, care, or management. As an appropriate analog for this survey, tools for pressure ulcers and sores have ultimately undergone development considering their associated morbidity and healthcare cost[129]. Of these tools, several have been developed to help predict pressure injury development[130, 131] with[132] or without[133] the standard Branden scale as a model feature. Similarly, future models could help predict the risk of suit contact or pressure injury by modeling crew anthropometry and biomechanics through continuous suit measurements.

Additionally, AI tools have been developed to visually stage and identify pressure injuries using CNNs[134, 135], ANNs[136], deep learning models[137], as well as multi-modal wound classifier networks[138]. Frameworks trained on pressure ulcer photos labeled for erythematous or necrotic features proved highly accurate in validation testing[139]. Similarly, a CNN proved useful in classifying wound injury features, with greatest accuracy for detection of necrosis[140]. Importantly, real world deployment of a faster region-based CNN (Faster R-CNN) trained to classify category I-IV pressure ulcer images over an 8-month trial reported a promising F1-score of 0.6786[141]. Researcher have also suggested that HELIOS LiDAR technology can improve vision-based ML classification of wound dimension measurements and presence of infection from diabetic foot ulcer images[142]. The ability to classify pressure injuries through digital image analysis, particularly monitoring wound healing, could prove useful during LDEMs.

CDSS systems to help manage pressure injuries are likely more important than prediction tools. Unfortunately, limited progress has been made since the early 2000s[143]. Of note, pressure ulcer images were used to train a U-net CNN for tissue segmentation, with the tissue classification output feeding directly to a CDSS to determine referral or care recommendation[144]. Next generation wound sensing platforms for point-of-care wound monitoring are also in development[145, 146], however, have undergone limited testing. Coupling data retrieved from next-generation bandages and vision systems with AI-based CDSSs will revolutionize wound management in the future. Ultimately, models trained on suit biometric data to prevent suit contact injury before it occurs is of utmost importance for future research.

*3.2 Rash, Abrasion, and Other Non-Cancerous Lesions*

While AI applications have been developed for the triage and diagnosis of cancerous skin lesions[147], their relevance for the previously outlined DRM and LDEMs is minimal and thus this survey will focus on tools related to non-cancerous skin lesions. Laying the foundation for later AI architectures, a knowledge share telemetry service known as Hippocra[148] and tools for proper annotation of dermatologic lesions[149] were developed. These works were followed by NN and ML models designed specifically for assistive dermatologic diagnosis[150, 151, 152] of numerous skin disorders. Methods such as metric learning and aggregation of multiple images from the same patient was found to increase the diagnostic accuracy of similar models for skin diseases[153]. Later developments ultimately focused on the combination of both image analysis and feature extraction with text-based information for improved diagnostic accuracy[154, 155, 156].

Additionally, explainable AI frameworks have been developed for assistive diagnosis of various dermatologic disorders[157, 158]. Of note, ImageQX was trained on digital images archived from a mobile dermatologic database to help improve diagnostic accuracy in poorer quality image sets[159]. Models trained on images captured from mobile phones would be of utmost relevance for LDEMs. More recently, vision-based AI systems such as AutoDerm[160] and SkinGPT[161], featuring more expansive datasets including space-related dermatologic disorders, have been reported. Unsurprisingly, vision transformer architectures have outperformed previously published CNNs and other fusion techniques for dermatologic diagnoses[162,163]. While AI-based dermatologic systems have been developed, real world validation of these applications as CDSSs, with prospective analysis of their clinical fidelity, is ultimately required before deployment. Models which report robust sensitivity and specificity while relying on limited image sets would be of utmost interest for compute and storage constrained LDEMs.

## 4. NEUROLOGIC

Numerous neurologic manifestations were highlighted by the late-Artrmis DRM outputs, including those conditions most likely based on frequency (insomnia, EVA-related paresthesia, headache) and most likely to cause TTL (insomnia). Investigations dating back to the late 1960s[164] have consistently highlighted significant loss of sleep alongside circadian disruption as conditions affecting crewmember health and performance[165]. Of note, sleep disturbances have been associated with detriments to astronaut physical and mental health including observed effects on cognition, visual alertness, and emotional wellbeing[166]. Both environmental factors and alterations in human physiology have been implicated in sleep disturbances onboard the spacecraft[167, 168, 169]. Resultingly, NASA has dedicated considerable resources to investigate both optimal sleep/wake schedules and effective countermeasures to optimize astronaut performance and ensure overall mission success[170]. Even with the initiation of work hour guidelines and countermeasures such as sleep medication and scheduled daytime naps, schedule creep and mis-timed light exposure are still reported[171].

Additionally, “space headache” is an underreported yet common complaint voiced by astronauts during space flight[172]. Previously associated with space motion sickness, headaches aboard spacecraft are correlated to increased $CO_2$ levels[173] and the general space adaptation syndrome[174]. Several AI applications surveyed below could transform preventative strategies and crewmember care for various neurologic conditions. Their architectures, capabilities, and relevance to the field are highlighted (**Table 5**).

### *4.1 Insomnia*

Disrupted sleep patterns and sleep deprivation are well-documented among astronauts in orbit and NASA has deemed these disruptions critical to mitigate in preparation for long duration space missions[175]. AI-powered tools to identify risk factors for sleep disturbances and insomnia are reported[176, 177, 178], including those powered by responses from digital sleep questionnaires[179]. A recently published review highlighted several sleep analysis tools[180] including frameworks using deep learning analysis of both ECG and respiratory patterns for automatic sleep staging[181, 182]. Groups have also applied ML techniques to both circadian signals[183] and triplet half-band filtered EEG signals[184] to accurately diagnose common sleep disorders. Furthermore, wearable devices[185, 186], capable of measuring both daily activity and sleep patterns, have shown robust correlation with traditional sleep monitoring techniques. These data were recently used to identify five insomnia-activity clusters through diachronic unsupervised ML with a convolutional autoencoder[187]. Continuously collected data from wearables will likely become a common information source for future CDSSs on these missions.

Chatbots or virtual agents designed to help manage sleep disorders have also been developed. The smartphone app called KANOPEE was designed to help individuals with sleep concerns. Using a decision tree algorithm, the virtual agent deploys a screening interview to provide sleep and behavioral advice[188]. Similarly, conversational agents for deployment of sleep coaching programs based on cognitive behavioral therapy for insomnia (CBT-I)[189] and engagement with patients diagnosed with insomnia[190] have been explored. Personalized chatbot applications may help with astronaut self-management of insomnia and other sleep disorders on LDEMs where limited connectivity may impede regular communication with caring aerospace medical professionals. It is highly likely that AI will be able to help monitor sleep with improved fidelity in spaceflight to optimize circadian cycling and improve sleep hygiene.

### *4.2 Paresthesia*

While AI tools have been developed for the evaluation of diabetic neuropathy[191], few evaluate contact paresthesias common amongst the astronaut population. Most AI efforts investigating peripheral neuropathies have focused on carpal tunnel syndrome (CTS) diagnosis. Models utilizing both hand grip data[192] and ultrasound images[193, 194, 195] have reported robust classification accuracy. ML prediction of CTS prognosis (1, 3, or 6 months) has also shown preclinical promise[196]. Further development of AI tools for the management of similar disorders will be of particular interest for deep space exploration missions given high prevalence of paresthesia after EVA.

### *4.3 Headache*

Headache was predicted to be the 6th most common condition (based on frequency) during the proposed DRM. Models for both the classification of common headache disorders using self-reported data acquired via questionnaire[197] and discrimination of tension headaches/migraines using clinical symptoms (nausea/vomiting and photo/phonophobia)[198] have been reported. More robust frameworks with CDSS integration[199, 200] have also been described. Web-based ML models for accurate headache prediction including the Headache Prediction Support System[201] and VikMigraine chatbot[202] have shown preliminary success; however, further clinical validation is ultimately required. Additionally, a computer-aided diagnostic agent powered by decision tree ML algorithms compared admirably to headache specialist interviews for diagnosis of migraine[203]. More recently, 17 variables collected via a questionnaire were modeled to classify headache symptoms, achieving the greatest diagnostic accuracy for both migraine and trigeminal autonomic cephalalgia when compared to physician diagnosis in validation testing[204]. Later, an ANN model successfully distinguished between seven migraine classifications with accuracy and precision greater than 97%[205]. The use of questionnaire or chatbot applications for headache classification during LDEMs will likely be crucial for prompt diagnosis. Tools for the management and care of these conditions, however, ultimately require further investigation.

## **5. AUDITORY AND VESTIBULAR**

Ear and sinus barotrauma was predicted to be the seventh most likely condition based on frequency, fourth most likely condition to cause TTL, as well as the seventh most likely condition to cause RTDC. Loss of pressurization onboard the spacecraft (particularly the ISS) is one of three emergent scenarios that have occurred during human spaceflight[206]. Commonly observed in diving[207], barotrauma is a major medical concern that results from expansion of gasses in the middle ear and sinuses[208] due to inadequate pressure equalization to the external environment[209]. Rapid pressure changes onboard the spacecraft are observed when pressurizing/depressurizing EVA suits, rapidly moving to areas of different volume within the habitat, or during forced or unexpected cabin depressurization[210]. Treatments for ear and sinus barotrauma have been suggested including oral/nasal decongestants and nasal vasoconstrictors[211].

Common symptoms related to barotrauma include both hearing loss and vestibular-related vertigo[212]. Hearing deficits and loss[213] are well-documented manifestations observed during short[214] and long duration spaceflight[215]. While hearing loss was thought to be primarily associated with elevated noise levels onboard the spacecraft, current data suggests there is no correlation, concluding that the etiology of hearing loss is likely multifold and unfortunately unknown[216]. High noise levels, however, have resulted in documented cases of headache and tinnitus onboard the ISS[217]. Vestibular symptoms are also commonly observed in-[218] and post- spaceflight [219] and are related to, among other factors, the altered gravitational environment in space[220]. With many associated clinical manifestations, AI tools to access the auditory and vestibular system are of utmost importance for long duration space missions and are discussed here (**Table 6**).

### *5.1 Tinnitus, Hyperacusis, Hearing-Loss*

Tinnitus and hearing loss are common symptoms of ear barotrauma[221]. ML models using audiometric data to first classify hearing loss[222] and then construct CDSS for identifying symptoms associated with tinnitus and vertigo[223] have been reported. For tinnitus retraining therapy, a CDSS consisting of ML driven predictive diagnostic models reported an average accuracy of 80% in preliminary testing[224]. Lee et al. also deployed four machine and deep learning models to predict patient recovery and prognosis from idiopathic sudden sensorineural hearing loss, though further testing is required[225]. More robust models for the clinical management of tinnitus ultimately require further investigation.

### *5.2 Vertigo, Nystagmus, and Dizziness*

Barotrauma is often associated with the development of dizziness and vertigo-like symptoms[226]. ML algorithms for prediction of common vestibular disorders have been reported, including models using responses from a diagnostic vertigo questionnaire[227]. A multi-language platform consisting of a medical database, user interface, and CDSS ML algorithm known as EMBalance was deployed for diagnosis of common vestibular disorders. EMBalance alone (without primary care clinician assessment) outperformed a primary care physician using the system as an assistive diagnostic agent[228]. Additionally, various ML algorithms have been deployed for classification of central and non-central dizziness[229]. Again, models to help manage or treat these conditions will be areas of active development before future LDEMs.

AI-tools utilizing eye tracking technology have also been developed for nystagmus characterization[230]. Of note, a deep learning model was trained on a nystagmus video set for clinical diagnosis of torsional benign paroxysmal positional vertigo (BPPV) with an accuracy of 85.73%[231]. Nystagmus detection models powered by infrared videos[232, 233] have also shown robust accuracy, with later models such as AnyEye additionally trained for pupil segmentation, eye tracking, and goggle slippage detection to improve classification accuracy[234]. Considering that nystagmography goggles are likely to be unavailable, traditional video monitoring systems would have greater applicability for deep space flight. In this regard, Look and Diagnose (LAD) is a proposed BPPV diagnosis system which utilizes RGB video for classification of six BPPV disorder classes. LAD achieved an average F1 score of 0.90 in preliminary testing[235]. Additionally, mobile applications such as the prototype VertiGo-App[236] or an Android-based nystagmus detection app powered by the Android (Google) eye tracking algorithm[237] have been developed for nystagmus identification from videos captured by smartphone cameras.

*5.3 Tympanic Membrane Imaging*

The advent of the digital otoscope allows deployment of AI-driven image processing models for automated middle ear disease diagnosis. Models for classification of tympanic membranes into normal and abnormal classifiers[238], segmentation of tympanic membrane structures[239], and detection of tympanic membrane size and perforation status[240, 241] have shown high diagnostic accuracy in early validation testing. More recently, a digital otoscopy video summarization and diagnostic labeling tool[242] was developed. Using these summarized otoscopy videos, a decision fusion mechanism was deployed to detect tympanic membrane abnormalities using tympanometry-derived measurements. Predictions from the ResNet-v2 (tympanic membrane images) and a RF classifier (tympanometry measures) underwent a majority voting-based decision fusion technique to reach a consensus diagnosis with a robust classification accuracy of 84.9%[243]. This work was then followed by Binol et al. who later published an automated tympanic membrane classifier known as OtoXNet. Here, OtoXNet learns features from otoscopy videos by constructing representative composite images to report a classification accuracy of 84.8%, outperforming both individual images and human-selected image frames[244]. Deployment of similar AI-tools alongside guided otoscope training for image acquisition would ultimately assist CMO evaluation of astronaut middle ears and alleviate the associated stress of often difficult-to-diagnose disorders.

*5.4 Diagnostic Tools for Ear Diseases*

Finally, AI tools have been also developed for the general diagnosis of middle ear diseases from otoscopic images using both machine[245, 246] and transfer learning techniques[247]. Of note, over 2400 otoendoscopy images were utilized to train the CNN DenseNet for diagnosis of middle ear infection, achieving an accuracy of 95% for middle ear effusion classification[248]. Additionally, Manju et al. compared numerous deep learning architectures for classification of four major middle ear diseases from RGB images, obtaining robust diagnostic accuracies[249]. Later, Chen et al. utilized 9 CNN-based models to diagnose middle ear disease from otoendoscopic images, with the best performing models ensembled for deployment on a mobile device[250]. Similarly, a CNN for Android smartphones was developed and trained using otoendoscopy images from 20 disease classes including barotrauma[251]. While further external validation and real-world clinical testing is required before deployment of these tools, the combination of both images/videos captured with a digital otoscope alongside assistive diagnostics agents will be immensely valuable during LDEMs.

**6. OPHTHALMIC**

Unsurprisingly, ophthalmic disorders were one of the most common clinical conditions predicted for this DRM. Vision loss and optic nerve swelling are among the most common ocular changes observed during spaceflight and have more recently been categorized into the multifaceted ocular condition known as spaceflight-associated neuro-ocular syndrome or SANS[252]. Other commonly observed ophthalmic abnormalities onboard the spacecraft include the development of disc edema, cotton wool spots, globe flattening, as well as choroidal folds [253, 254, 255]. While less common, ophthalmic emergencies, including corneal abrasions, ulcers, and foreign bodies are anticipated to occur during space exploration missions[208]. These ocular emergencies are considered “red” or high-risk events due to near-immediate astronaut compromise with their occurrence and wide range of causative agents (Lunar dust, chemical injury) evident onboard[256]. Resulting ophthalmic manifestations were noted as being both most likely conditions based on frequency (eye irritation, corneal abrasion, ulcer) and most likely to cause RTDC (foreign body in eye, eye irritation, corneal abrasion, ulcer, chemical eye burn) for the proposed DRM. Tools to triage and diagnose these emergent and non-emergent ophthalmopathies are highlighted in this review (**Table 7**).

Numerous AI-based CDSSs for the diagnosis of ophthalmic conditions have been reported. ML models to predict eye disease classification from EHR data[257], web-based CDSSs with a decision tree framework for triage of ophthalmic symptoms[258], and NLP frameworks for ophthalmic disease diagnosis[259] have been reported. General diagnostic tools and LLMs such as ChatGPT-3 and the Isabel Pro Differential Diagnosis Generator (Isabel Healthcare, Ann Harbor, MI, USA) have also been assessed for accuracy on 10 ophthalmic case reports. Here, ChatGPT outperformed the Isabel system, identifying the diagnosis in 9 of 10 cases versus 1 of 10 for the Isabel system[260]. Additionally, an optimized ophthalmic disease diagnosis framework utilizing both NLP and a transformer architecture known as NEEDED outperformed both CNN and LSTM models in real-world validation testing[261]. Of utmost relevance, EE-Explorer is a triaging system using both metadata and ocular surface images collected via smartphones for ophthalmic diagnosis. During external validation testing, the ophthalmic triaging model achieved a robust AUC of 0.988. Importantly, the primary diagnostic model displayed great performance for diagnosis of relevant ophthalmic pathologies including corneal diseases (ulcers, abrasion, foreign body) and ocular trauma (including chemical injury)[262]. Considering the training data set (smartphone images) and diagnostic accuracy on space-relevant ocular injuries, EE-Explorer would immediately become a candidate framework for future LDEMs.

*6.1 Optical Coherence Tomography (OCT)*

AI tools for OCT-guided analysis, a diagnostic capability aboard the ISS, were widely reported in the literature including models for the diagnosis of dry-eye disease[263, 264], identification and grading of superficial punctate keratitis using fluorescein-stained images[265], quantification of lower tear meniscus height[266], segmentation of healthy and keratoconus cornea[267], diagnosis of keratoconus[268], and prediction of keratoconus progression[269]. Additionally, anterior segment OCT images were used to develop a deep learning network for corneal disease diagnosis with an AUC of 0.99[270]. More recently, novel hybrid-transformer models such as the lesion-localization convolution transformer (LLCT)[271], Swin-poly Transformer[272], Structure-Oriented Transformer (SoT)[273], and TranSegNet model[274] have outperformed both CNN and traditional vision transformer models for OCT image segmentation and retinal disease identification. Combining these AI-tools with the OCT imaging capability available on the ISS and possibly during LDEMs will prove valuable for the diagnosis of many ophthalmic disorders.

*6.2 Keratitis, Corneal Lesions, and Systemic Health Predictions*

Corneal lesions are often associated with the development of infectious keratitis. ML models for the accurate diagnosis of infectious[275] and fungal keratitis[276] from corneal images have shown comparable accuracy to non-corneal specialists. Models for analysis of anterior segment slit-lamp images for diagnosis of infectious keratitis, including the DeepKeratitis model[277] and KeratitisNet[278], have demonstrated robust classification accuracy in preliminary testing. Additionally, a CNN was trained for classification of corneal lesions into active corneal ulcers (with infection) or healed scars from external corneal photographs, achieving an AUC of 0.9474 during external validation testing[279]. Retinal fundus imaging models have also been deployed for analysis of overall patient health including prediction of cardiovascular risk factors and major adverse cardiac events[280]; detection of branch retinal vein occlusion[281]; prediction of hemoglobin concentration (g/dL) and screening for anemia[282]; detection of renal functional impairment[283], chronic kidney disease[284], and hepatobiliary disease[285]; as well as prediction of over 50 other patient health parameters[286].

Retinal photographs have also been used to train predictive health models. Of note, Rim et al. deployed deep learning to predict a number of systemic biomarkers from retinal photographs. Unfortunately, 37 of 47 biomarkers failed external validation testing[287]. External photographs of the eye were even used to train deep-learning systems for diagnosis of diabetic retinal diseases[288]. Nusinovici et al. also developed deep learning models to predict both age and overall morbidity and mortality risk using retinal photographs. Those individuals screened and placed in the 4th quartile ultimately had a 67% greater risk for 10-year all-cause mortality in comparison to those in the 1st quartile[289]. While further validation is required, the use of ocular imaging techniques to assess multiple organ systems and even overall health during LDEMs could be of utmost clinical value.

## 7. MUSCULOSKELETAL

Musculoskeletal abnormalities were highlighted as medical conditions that would affect TTL (EVA-related shoulder injury and upper, lower, back, and neck strains) as well as cause RTDC (wrist fractures). It is well known that microgravity experienced during spaceflight causes severe bone and muscle loss that must be counteracted through regimented exercise prevention programs[290]. With more recent muscle deconditioning data acquired during longer duration missions on the ISS, researchers have now suggested even higher-load resistance exercises to better counteract these changes[291]. Accordingly, numerous inflight musculoskeletal injuries have been documented to date including those to the upper (hands, elbow, shoulder) and lower extremities (feet)[292]. The leading causes of musculoskeletal injury (hands and fingers) on the ISS are related to EVAs (particularly suit components), exercise programs, and general movement throughout the habitat[293]. While ligamentous sprains of the hands, knees, and ankles have been empirically observed, these injuries have been considered mild and did not require surgical intervention. Injuries that are more concerning for LDEMs include those which cause astronauts to become non-weightbearing and therefore unable to perform necessary exercise programs, such as in the case of high-grade ankle or knee sprains[208]. Additional countermeasures against musculoskeletal injuries have been explored including stretching and conditioning programs, modifications to equipment, such as improvements to spacesuit ergonomics, as well as training programs to prepare astronauts for management of these high likelihood occurrences[294]. Furthermore, astronauts adapting to microgravity commonly experience back pain[295] resulting from spinal elongation and disc expansion[296, 297]. Additionally, while bone fracture risk is particularly elevated post-flight due to bone mineral density losses observed during spaceflight[298, 299], inflight fractures are also concerning during LDEMs[300]. Ultimately, AI tools developed to assist in the diagnosis and management of musculoskeletal conditions in terrestrial medicine have possible applications during exploration spaceflight and are extensively detailed below (**Table 8**).

*7.1 Soft Tissue Injury - Upper Extremity*

Prediction models have been developed for musculoskeletal injuries in both occupational[301] as well as sports-related settings[302], however, lack external validation and therefore could not be recommended for clinical use. For diagnosis of shoulder injuries, numerous AI-driven tools have been developed. These tools range from general LLM such as ChatGPT-3.5, utilized to deliver medical information such as the appropriate examination and treatment for shoulder impingement syndrome (SIS)[303], to more targeted frameworks. Of utmost relevance, numerous groups have investigated the use of ML and deep learning models for the diagnosis of rotator cuff injury[304, 305, 306] and scapulohumeral periarthritis[307] with robust accuracy. Anteroposterior radiograph images were also analyzed via a CNN and DSNT layer to predict landmark coordinates for critical shoulder angle (CSA) calculation and determination of rotator cuff tears or glenohumeral osteoarthritis within the standard error of clinical measurement[308]. While a deep learning model was successfully trained on shoulder ultrasounds images for the accurate diagnosis of rotator cuff injury[309], further efforts in this domain are ultimately warranted[310].

Interestingly, a Microsoft Kinect V2 Motion Sensor device, used to capture active shoulder movements, coupled with a SVM model, diagnosed shoulder pain (peri-shoulder or rotator cuff muscle injury) with similar accuracy to a physician physical exam[311]. Video monitoring tools to accurately assess shoulder injuries based on critical movements could help automate diagnosis of astronaut upper extremity injuries. Furthermore, a mobile application with a ML model coupled with telemetry data from a smartwatch was developed for the accurate determination of four shoulder range of motion arcs. The group suggested that determining range of motion could be critical for the early detection of shoulder pathologies and help examine the efficacy of exercise programs or physical therapy[312]. Additionally, inertial sensor data from smartwatches[313, 314] have been used to train shoulder range of motion ML models with great accuracy. The fuzzy logic approach was then used to suggest shoulder rehabilitation exercises based on shoulder range of motion and muscle strength[315]. Clinical management of upper extremity strains through directed rehabilitation programs, powered by AI models, will be integral for expedited injury recovery during space missions.

While lateral elbow tendinopathy (LET) or tennis elbow is a common upper extremity overuse injury, few AI tools have been developed for its diagnosis or management. Of note, fuzzy logic analysis of elbow strength, as assessed by elbow flexion angle and torque, was used to predict lateral epicondylitis risk[316]. Droppelmann et al. also used a total of 30,007 ultrasound images from 4,324 exams of the common extensor tendon to train ML models for binary and multilayer classification of degenerative tendon pathology[317]. Furthermore, AI has been shown to improve the fidelity of ultrasound-guided analgesics delivery. Systems such as the ScanNav Anatomy PNB (Intelligent Ultrasound, Cardiff, United Kingdom) utilize AI to highlight integral structures during peripheral nerve block delivery[318] and may help CMOs deliver injections when caring for various injuries.

*7.2 Soft Tissue Injury - Lower Extremity*

While several tools have been developed for the prediction, classification, and rehabilitation of chronic lower extremity musculoskeletal pathologies such as knee osteoarthritis[319, 320, 321, 322], tools relevant to lower extremity musculoskeletal strains are lacking. Of note, ML models to predict running injuries in adult athletes[323] and lower extremity injury risk in National Football League (hamstring, quadriceps, ACL)[324] and National Basketball Association (quadriceps, groin, calf, hamstring)[325] players have been developed. Further, a deep-learning system based upon layered CNNs was utilized to predict risk of sports injury, provide an injury prevention protocol, and diagnose a given injury with greater fidelity than other ML methods[326]. Similar models which could incorporate the number of EVAs, amount of time on the lunar surface, and other astronaut physical activities may prove useful in predicting future injury risk.

Few AI-based CDSSs have been proposed for the diagnosis and management of common lower extremity injuries. Of note, an expert system for the diagnosis and proposed care for common knee pathologies was developed, however, performance was not reported[327]. A CDSS consisting of a multi-agent-based knee diagnostic system using patient-reported symptoms outperformed traditional fuzzy logic network algorithms for treatment recommendations, however, underwent limited-to-no validation testing[328]. Further, an expert system for diagnosis of common ankle pathologies using decision tree algorithm and detailed knowledge base with the SL5 Expert System was also proposed, again lacking performance data[329].

With both MRI and CT being the preferred imaging modalities for detection of lower extremity injuries, both of which are unlikely to be utilized during LDEMs, most AI-tools developed to date have limited relevance in capability-limited LDEMs. Of note, AI frameworks have been trained on radiographs for the identification of ACL tears, joint effusion, and abnormal femoral notches[330], detection of lower extremity abnormalities of the knee, ankle, hip, and feet[331], as well as diagnosis of discoid lateral meniscus tears[332]. Long et al. proposed a deep learning model for accurate segmentation and classification of diseased knee ultrasound images using snake processing and multi-channel learning[333]. For diagnosis of Achilles tendon injury, a RF selection-based SVM was used to accurately diagnose Achilles tendinopathy from ultrasound images with a robust AUC of 0.99[334]. The recent development of movement-based segmentation models of ligaments and tendons may improve diagnostic capabilities of ultrasound for numerous musculoskeletal pathologies in the future[335]. These models, trained on ultrasound images, will be of high priority for LDEMs, as this imaging modality is a common component of most, if not all, proposed medical kits.

Finally, gate data acquired from inertial sensors and/or computer vision has been used for both gait analysis from video[336] and the detection of sports-related ACL injuries[337, 338, 339]. Use of gate-analysis from computer vision during treadmill exercises on LDEMs would be an effective method for early detection and prediction of lower extremity pathologies. Furthermore, AI-based tools for management and rehabilitation of lower extremity musculoskeletal injuries have been developed including the deployment of SVM algorithms on movement signals during walking or running[340], computer vision layered CNNs for rectus femoris tear rehabilitation[341], and a Bayesian linear regression and NN models to predict Achilles tendon rehabilitation outcome[342]. Interestingly, Qiao et al. determined that rehabilitation of muscle strains under AI supervision led to a reduction in muscle restrain and improved recovery in patients[343]. A review by Lloyd et al. later detailed how personalized musculoskeletal modeling through computer vision, wearable devices, and motion-based capture systems can be used to extrapolate internal musculoskeletal strain with instantaneous feedback[344]. Next-generation wearable sensors and computer vision could ultimately help guide rehabilitation programs during these missions, especially during times of connectivity and communication loss.

*7.3 Soft Tissue Injury - Axial Skeleton*

Back and neck sprain were conditions predicted to affect TTL during the proposed mission. While CDSSs are ultimately lacking in this space, ML models have been deployed to improve the accuracy of self-referral to primary care for patients with low back pain[345] and improved classification accuracy of lower back pain symptoms[346]. Expert systems designed for both the diagnosis of low back[347] and neck pain[348] have also been reported, however, with limited-to-no validation testing. Furthermore, text-based information recorded from a patient questionnaire was used to train decision tree algorithms for the accurate diagnosis of spinal conditions, achieving a diagnostic accuracy of 72% in comparison to the physician-assigned diagnosis[349].

While not common practice in terrestrial medicine, several imaging diagnostic models trained on ultrasound images have also been developed for assessment of neck and back pain. These include a spinal volumetric reconstruction model using a deep residual U-shaped network for the diagnosis of lumbar pathologies[350] as well as shear wave velocity ML models for the accurate detection of neck muscle dysfunction[351]. AI-driven models for the assessment of spinal radiographs have also been developed[352, 353, 354], including deep learning models for the diagnosis of lumbar spondylolisthesis[355] and cervical spondylotic myelopathy[356]. Additionally, a hybrid transformer network was constructed for the accurate estimation of the Cobb angle from X-ray images for improved detection of cervical spondylosis[357]. Models for the accurate diagnosis of cervical degenerative disease[358] as well as C-spine injury[359] from lateral cervical spine radiographs were also evident in our literature search. More recently, NLP of radiologic reports using the Bidirectional Encoder Representations from Transformers (BERT, Google) model was used to annotate lumbar spine images for deep learning on the ResNet-18 architecture with relatively robust accuracy[360]. Large, annotated image sets will be the basis of future CDSSs for axial skeleton injuries.

Models to predict improvement in neck pain[361], change in cervical range of motion following rehabilitation[362], or even treatment outcomes, such as in patients receiving trigger-point lidocaine injections[363], have been described. Additionally, Salinas-Bueno et al. utilized a camera-based head tracking model, deployed on a mobile application, to successfully monitor patient neck range of motion[364]. Computer vision models capable of matching the performance of inertia sensors would be valuable for data-driven rehabilitation and monitoring programs aboard spacecraft.

Neck and back pain self-management applications were also widely reported in the literature. To begin, patients with chronic back pain underwent a 5-week pilot study following exercise recommendations from MyBehaviorCBP, a ML mobile application using both self-reported and sensor-derived physical activity data. Interestingly, patients actualized the app recommendations more commonly compared to those provided by a general practitioner[365]. Further, the Well Health mobile application (Well Health Technologies Corp., Vancouver, British Columbia), powered by multilayer perceptron ANNs (MLP-ANN), utilizes patient-reported symptoms to provide personalized neck and back rehabilitation programs. An observational study reported an overall positive response to app use with an increase in daily exercise time amongst participants[366]. The mobile application known as selfBACK is a well-reported decision support system for the self-management of lower back pain[367]. Clinical trial testing reported improvement in the Roland-Morris Disability Questionnaire (RMDQ) score when patients utilized selfBACK in combination with physician guidance (52%) versus those who only received advice from their clinician (39%)[368]. Recently, the selfBACK application was reported effective even in the setting of severe depression[369]. Similarly, a mobile messaging app known as Secaide was assessed in a randomized clinical trial for the management of chronic shoulder, neck, and back pain, with 75% of users reporting improvements in their chronic pain[370]. Finally, the AI-driven digital application known as PainDrainer (Lund, Sweden) was also developed for the self-management of chronic neck and back pain. During a 12-week open-label trial, patients reported an increase in physical function, reduction in depression and anxiety, alongside a decrease in pain catastrophizing scale (PCS) scores[371]. Integration of these tools into a next-generation medical system will be valuable for the self-management of common musculoskeletal injuries during LDEMs. Unlike most applications reported throughout this manuscript, the aforementioned AI tools for common neck and back pain have undergone rigorous validation testing during human clinical trials and thus could be immediately considered for preliminary testing aboard the ISS.

*7.4 Bone Fracture - Wrist*

Numerous AI-based tools have been developed for fracture detection and osteoporosis risk assessment[372, 373, 374, 375, 376], however, have limited relevance to the astronaut population. For identification of common wrist fractures from radiographs, VGG-16[377], a deep CNN[378], Inception-V3[379], a Faster R-CNN[380], deep learning models[381, 382], a feature pyramid network[383], NNs[384], deep NNs[385], as well as ensemble[386] and transfer learning[387] models have been developed with remarkably robust classification accuracies. Of note, a deep learning system, trained on only 524 wrist radiographs, performed admirably in comparison to radiologists[388]. Models relying on smaller training sets may prove useful for LDEMs with data storage constraints. Additionally, Seth et al. recently explored the use of ChatGPT for the delivery of medical advice for the management of scaphoid fractures using patient enquiry prompts with relative success[389]. While these data show promise, the creation of mission-specific LLMs will likely be necessary considering compute and connectivity constraints on LDEMs.

Frameworks for the detection of scaphoid (ML[390], CNN[391, 392, 393, 394], deep CNNs[395, 396, 397]), distal radial (deep CNN[398], ensemble models[399], NNs[400]), and combined radial/ulnar (Faster CNN[401], VGG-16[402]) fractures have also been extensively described. Of note, a deep learning pipeline for distal radius fracture detection known as DeepWrist was evaluated on a challenge set including only distal radial fractures that required CT for confirmatory diagnosis. The group determined that while DeepWrist displayed robust fracture detection accuracy in the general radiographs (99%), accuracy in the challenge set dropped to 64%[403]. Resultingly, more extensive validation testing is likely necessary before real-world deployment of similar models. Several AI-tools to assess wrist trauma, bone healing, and fracture rehabilitation have also been developed. Shinohara et al. performed transfer learning on pretrained vision models for the detection of palmer 1B triangular fibrocartilage complex injury using ultrasound images[404]. Models to stage distal radius fracture healing[405] and predict bone healing after limb fracture repair surgery[406] have also been described. While surgical repair of fractures is likely not possible, bone healing after proper reduction and splinting/casting could be monitored via a similar system. Furthermore, a ML model for accurate remote brace fitting for patients with wrist injury outperformed manufacturer recommendations[407]. Management of wrist fractures will require proper splinting/casting and accurate remote monitoring for overall mission success. Therefore, deployment of similar models within an all-encompassing CDSS are ultimately warranted, especially for mission segments with increased risk of wrist-related injuries such as spacewalks.

**8. INFECTION-ASSOCIATED MEDICAL CONDITIONS**

Astronaut susceptibility to microbes, microbe physiological changes, and observed antibiotic resistance are well-documented space flight observations[408]. Resultingly, several infection-associated medical conditions including bacterial skin and soft tissue infections (SSTIs)[208] (RTDC and LOCL), acute diarrhea[409] (TTL and RTDC), urinary tract infections (UTI)[410] (LOCL), and dental abscess[208] (LOCL) were suggested for the proposed DRM. Bacterial SSTIs are commonly observed onboard the ISS[208]. Increased risk for these infections is related to changes in skin microbiota which result from microbial exchange between astronauts and their environment[411] alongside stressors unique to long duration space travel such as dry washing[412]. Additionally, documented cases of acute diarrhea during human spaceflight date back to the Apollo 17 missions[413], with most cases secondary to food, medication, or infection[409]. Much like skin, changes to the gut microbiota that occur during spaceflight are also implicated here[414, 415, 416]. Of note, recent improvements to the medical kit onboard the ISS have made clinical management of gastrointestinal disorders, among other conditions, possible[417].

Furthermore, adaptations to the renal system during human spaceflight have been well researched since the 1970s[418]. Of note, 10% of astronauts during the shuttle program experienced some form of genitourinary complication during flight[419]. Both increased urinary retention[420] and catheterization (associated with space adaptation syndrome) are documented risk factors for the development of

UTIs[403]. While renal calculi also increase the risk for UTI and other genitourinary complications, they have not been observed inflight to date[421]. Due to their associated risks, numerous mitigation strategies for urologic complications are in active development[422].

Additionally, reports of cosmonauts and US astronauts experiencing dental pain and lost crowns or fillings during spaceflight are reported; however, these are not considered true dental emergencies[423]. Dental emergencies on the ISS are evidently rare due to extensive preflight exams that occur[208]. Recent research, however, suggests an increased risk for periodontitis and dental carries, among other dental conditions, during LDEMs[424]. With these data, reports suggesting overall risk, optimal countermeasures, and mitigation strategies for those most common dental conditions in spaceflight have been published[425, 426]. Importantly, AI-tools have been developed to prevent, diagnose, and manage infection-associated medical conditions in terrestrial medicine (**Table 9**). Considering that these conditions can complicate into life-threatening sepsis[427], considerable resources will likely be deployed for their management.

*8.1 Bacterial Skin and Soft Tissue Infections*

Bacterial skin and soft tissue infections (SSTIs) were proposed to cause RTDC or LOCL. AI frameworks for the rudimentary segmentation of infectious cellulitis[428] have been described. These models then became the basis of expert systems for the accurate diagnosis of infections and recommended antibiotic treatments using patient reported symptoms[429] or descriptive skin information[430]. Several vision models have also been developed for the diagnosis of various skin infections through k-means (image processing and segmentation) and SVM (classification) algorithms[431] as well as CNN architectures[432, 433]. Necrotizing fasciitis image datasets, first used to train the YOLOv3 ANN[434] architecture, were later the foundation for CDSSs with the ability to predict necrotizing soft-tissue infection mortality[435] and individualized treatment effects[436]. Additionally, several AI-based tools for the analysis of Gram stains and bacterial cultures were assessed in the review by Smith et al.[437] Of importance, the pre-trained Inception-V3 CNN was trained on over 100,000 blood smear gram stains for the automated detection of gram positivity and shape with robust accuracy[438]. Furthermore, Radhakrishnan et al. developed a hand-held imaging device using multi-wavelength UV LEDs for multi-spectral image capture followed by ML classification for the rapid detection of SSTIs with greater than 85% accuracy in initial clinical testing[439]. Tools such as those described may be useful for accurate detection of infectious microbes and appropriate antibiotic stewardship aboard spacecraft.

*8.2 Gastrointestinal - Acute Diarrhea*

The most common etiologies of acute diarrhea in terrestrial medicine are both infectious and non-infectious[440]. While acute diarrhea in astronauts is likely caused by non-infectious etiologies (space sickness), some of the AI tools used to characterize acute diarrhea are highlighted here. Both expert systems for the diagnosis of bowel disease[441] and fuzzy NNs trained on blood and biochemical test results for accurate diagnosis of acute cholecystitis, gastroenteritis, and pancreatitis[442] have been reported. Sanaeifar et al. developed an online CDSS tool known as DxGenerator for the accurate diagnosis of 120 diseases affecting the gastrointestinal system and causing the common symptom of abdominal pain (often associated with symptomatic diarrhea). DxGenerator uses both NLP and the MetaMap tool for convergence with the unified medical language system (UMLS) knowledge base. In preliminary validation testing, DxGenerator outperformed the ISABEL differential diagnosis generator on 172 clinical vignettes and, to date, is considered the most robust CDSS for symptomatic abdominal pain[443]. Models for the analysis of stool form and color[444, 445] as well as hydration status[446], common clinical measures used for diagnosis and care of acute gastrointestinal conditions, have also been developed. These tools may make continuous gastrointestinal monitoring over the course of LDEMs possible.

*8.3 Urinary Tract Infection*

Numerous factors of spaceflight (urinary retention, kidney stone formation) increase the risk for developing urinary tract infections (UTIs)[208]. Both ML algorithms[447, 448] and ANNs[449, 450] have been trained for the prediction of UTI using a variety of clinical variables. UTI-focused CDSS tools have also been developed including models for the preliminary diagnosis of UTI based on identifiable physical symptoms[451] or models which simplify classification of urinary symptoms into either cystitis or pelonephritis[452]. Importantly, a UTI CDSS utilizing an interpretable decision tree ML framework underwent prospective evaluation in 36 primary care practices over a 4-month period. For the nearly 5000 observations made, successful UTI treatments significantly increased to 83% when the CDSS was used by general practitioners[453].

Tools to assess kidney stones, a top risk factor for developing UTIs, have also been developed. A model of early kidney stone detection achieved an AUC of 0.996 for kidney stone presence with an accuracy of 97.1% when predicting stone type[454]. Additionally, ANNs have been developed to predict spontaneous ureteral calculus passage with robust accuracy[455, 456]. Models to discriminate between infectious and noninfectious urethral stones, while present[457], are lacking in published literature. Further, both ML and ANN models have been examined for the prediction of urosepsis development in patients with UTI using blood biomarkers and patient demographic data[458]. Predictive frameworks trained specifically on data derived from patients with upper renal calculi[459] and obstructive pyelonephritis[460] were also evident in literature.

Urinalysis is a mainstay clinical evaluation used to diagnose UTI and other urinary complications. Algorithms for the automated detection of UTIs[461] including those that predict the risk of urinary tract infection based on urine turbidity and blood cell counts[462] or microscopic and chemical analyses[463] have been developed. Furthermore, the APAS® Independence automated urine culture tool was recently evaluated for automated interpretation of urinary cultures, achieving robust sensitivity and specificity of 0.919 and 0.877, respectively, in clinical testing[464]. Interestingly, a smartphone application with an image recognition framework coupled with a lab-in-a-Cup hybrid urine analyzer was recently developed to accurately measure urine chemistries[465]. Next-generation, point-of-care urinalysis devices would help triage and diagnose numerous urinary disorders during LDEMs. AI tools have also been developed to improve antibiotic selection for treatment of UTIs and promote antibiotic stewardship[466, 467, 468], even in the setting of complicated UTIs[469]. Further investigation of CDSSs that utilize measurable clinical data to help guide antibiotic therapy are warranted.

*8.4 Dental Abscess*

Dental abscesses are frequently the result of dental caries, trauma, or failed root canal treatment[470]. CDSSs for diagnosis and management of dental caries and abscesses have been proposed, such as a fuzzy logic expert system[471], a diagnostic agent based on NLP of dentist notes[472], and a SVM model with a self-attention network[473]. Frameworks for the identification and analysis of dental caries from radiographs have been developed, including both CNNs[474, 475, 476] and an ANN[477]. A faster R-CNN for the automated detection of periodontal disease[478] and CNN for the classification of teeth as decayed, root-canaled, restored, or healthy[479] have also been examined. More recently, an attention-based vision transformer model[480] and modified U-shaped network[481] have been proposed for the improved dental carie classification from tooth radiographs. Of utmost relevance for deep space missions, a vision transformer model for detection of dental caries using only 300 images captured from a smartphone was developed. This model, known as CaViT, achieved sensitivities of 100%, 91%, and 95% for prediction of advanced caries, early caries, or no caries, respectively[482]. Additionally, over 5600 RBG oral images were used to train an image classifier model with a multispectral and position attention mechanism. The model, known as CariesFg, achieved an accuracy of 68.36% in validation testing[483]. Models capable of analyzing images captured with a basic smartphone and not reliant on common terrestrial diagnostic imaging techniques could be easily integrated into future CDSSs on LDEMs and help with dental diagnoses.

Apical radiolucencies and lesions manifest secondarily to infection-associated oral lesions. A deep CNN[484], AlexNet/SVM architecture[485], and deep learning model[486] were validated for detection of periapical and apical lesions from radiographs. CNNs, including DenseNet121[487] and InceptionV3[488], also achieved robust clinical accuracies for the detection of common oral lesions. Furthermore, tooth fractures can lead to the development of dental abscess at the dental root[489]. An adaptive CNN[490] and deep learning model based on the DetectNet CNN architecture[491] were deployed for the detection of third molar complications and vertical root fractures, respectively. These AI-tools would provide invaluable diagnostic insight for early identification of oral manifestations and dental abscess prevention in this setting.

*8.5 Bacteremia and Sepsis*

Numerous conditions predicted for the DRM could ultimately progress to bacteremia or sepsis without proper clinical intervention. Extensive work has ultimately been conducted to develop both predictive and diagnostic sepsis frameworks. To begin, several ML frameworks have been developed for more accurate triage of sepsis patients[492, 493] visiting emergency care centers. Considering that the early identification of sepsis is critical for timely care in terrestrial medicine, numerous AI algorithms have been developed to predict early onset of sepsis[494, 495, 496, 497, 498, 499], severe sepsis[500], septic shock [501, 502], and sepsis severity[503], even without culture results[504]. Of note, gradient boosted trees were designed to predict sepsis onset using only six vital signs, achieving a predictive AUROC of 0.84 and 0.83 for 24 and 48-hours before sepsis onset, respectively[505]. Further, Kijpaisalratana et al. compared RF and gradient boosting ML models to LR for the early detection of sepsis using only basic vital sign and demographic data from over 133,000 ED visits. The RF algorithm reported the greatest AUROC of 0.931, outperforming traditional reference models[506]. Interestingly, in a prospective open-label cohort study, 106 pre-selected features and an XGBoost ML algorithm could predict an early sepsis diagnosis with an accuracy of 82% ± 1%, outperforming the common Sequential Organ Failure Assessment (SOFA) score[507].

Several models have also been developed to improve sepsis critical care including models to suggest optimal treatment[508], delivery of both vasopressors[509] and IV-fluids[510], and predict bedside fluid response from echocardiographic parameters detected by ultrasound[511]. Interestingly, use of the Epic Sepsis Prediction Model, a sepsis alert system powered by proprietary prediction algorithms, ultimately was no different in time to initial antimicrobial therapy in comparison to the SIRS-based electronic alert available on the same platform[512], however, further investigation is warranted. Models to predict sepsis-related mortality[513, 514, 515, 516] as well as patient length of stay[517] have been reported. Considering the severity and number of primary conditions which can progress to sepsis, considerable compute will be dedicated to infection-associated conditions. Predictive sepsis models utilizing only basic vital sign data would be of critical relevance to future CDSSs.

**9. GYNECOLOGIC**

The negative impact of microgravity (as well as radiation exposure) on the female reproductive system have long been suggested[518]. Due to a lack of evidence, however, the magnitude of these effects during LDEMs is considered unknown[519]. To date, additional preflight certifications, menstruation control, and contraception are some of the unique operational considerations learned from both the Mir and Shuttle era for women in space[520]. While the risks and benefits of hormonal supplementation in spaceflight are complex, especially considering the hormonal impact on bone mineral density, venous thromboembolism risk, ovarian cyst production, vulvovaginal candidiasis, co-management by astronauts and physician/pharmacy teams helps optimize the use of this therapy[521]. With females making up 50% of the astronaut corps for the upcoming Artemis missions, we anticipate a marked expansion of our understanding of sex-specific spaceflight-induced gynecologic, reproductive, cardiovascular, and musculoskeletal adaptations[522].

Uncontrolled abnormal uterine bleeding (AUB) was highlighted as one condition capable of leading to LOCL during the proposed DRM. Any disruption to normal menstrual proliferation, decidualization, vasoconstriction, and repair can lead to AUB. AUB etiologies are divided into structural and non-structural causes. These include polyps, leiomyoma, malignancy/hyperplasia, as well as adenomyosis (structural) alongside ovulatory dysfunction, disorders of the endometrium, coagulopathy, iatrogenic, or other causes not yet classified (non-structural)[523]. Resultingly, acute AUB onboard requires immediate medical intervention[524]. Numerous pre- and in-flight considerations are made with respect to AUB. Of utmost importance, pre-flight transvaginal ultrasound is performed on all female astronauts with AUB to detect possible structural causes. Screening for polycystic ovarian syndrome (PCOS), family history of bleeding disorders, and iron deficiency is also performed. Menstrual suppression and induction of amenorrhea through either combined hormonal contraceptives or the levonorgestrel IUD are often utilized by female astronauts. Due to the lack of advanced surgical options in-flight, pharmacological therapy and vaginal tamponade would be the first-line interventions for AUB onboard the spacecraft[525].

Findings from terrestrial medicine would suggest that the most likely causes of AUB in the female astronaut population (perimenopausal women over 40 years of age) may still include a structural cause, oligoovulation, or pregnancy. Less likely include a gynecologic malignancy or precancerous lesions, polycystic ovarian syndrome, or other causes of hormonal imbalances (more common in the adolescent population)[526]. Accordingly, those AI-tools for diagnosis and management of relevant AUB-related conditions are outlined below (**Table 10**).

CDSSs for the diagnosis of gynecologic disorders associated with AUB have been developed. An expert system for the diagnosis of uterine myomas and ovarian cysts[527], ML models for the accurate diagnosis of endometriosis[528, 529], as well as models for the general diagnosis of gynecologic diseases[530, 531] have shown preliminary success in early validation testing. While not a CDSS, Irene et al. proposed a smart menstrual cup with chaos game optimized CNN for the automated detection of menstrual flow that exceeds a certain volume[532]. Similar tools may be critical for overall female astronaut health during future LDEMs.

*9.1 Assistive Transvaginal and Abdominal Ultrasound*

Models for the automated analysis of transvaginal and abdominal ultrasound images were also reported. Both an endometrial segmentation and thickness measurement model[533] as well as a ML model for classification of endometrial tumors[534] have undergone preliminary validation testing. Of note, a CNN for classification of deep pelvic endometriosis from vaginal ultrasound images demonstrated a robust diagnostic accuracy of 90.68%[535]. More recently, CNNs were trained for the detection of intrauterine adhesions from transvaginal and transabdominal ultrasound images[536]. Importantly, when assistive diagnostic models are used by junior ultrasonographers (a reasonable surrogate for a CMO in spaceflight) diagnostic accuracy, sensitivity, positive and negative predictive values of gynecologic pathology are improved[537]. Models for the diagnosis of uterine adenomyosis[538] and detection of uterine fibroids[539] were also evident in the literature search. Tools for the automated analysis of ultrasound images will be critical for the assistive diagnosis and triage of gynecologic medical conditions during these missions. Models which utilize the less invasive transabdominal approach will ultimately be preferred.

*9.2 Malignant Gynecologic Prediction Models*

Prediction models for diagnosis of cervical and endometrial cancer not reliant on histopathological image analysis[540, 541, 542] have been developed. Of utmost relevance, Erdemoglu et al. trained several ML models for the prediction of cancerous and precancerous endometrial neoplasia using demographic information, menopausal status, presence of bleeding, medical comorbidities, and endometrial thickness[543]. To predict endometriosis-associated cancer, Chao et al. deployed NLP and a LR model to identify the top ten demographic and clinical features associated with cancer progression. Those ten features trained on a gradient-boosting ML model achieved a sensitivity and specificity of 86.8% and 96.7%, respectively[544]. Furthermore, a CDSS powered by various ML models were trained on 58 clinical features from nearly 1000 patients to predict the risk of non-benign postmenopausal endometrial lesions with robust accuracy[545]. Models for triage and risk stratification for gynecologic conditions can potentially be relevant for the long-term management and maintenance of astronaut health post-flight.

## 10. TRAUMA AND EMERGENCY

Amongst all factors considered for space exploration, emergency care of crewmembers in the event of serious, traumatic injury will be of the utmost importance given that all historic crew mortality has been attributable to vehicular failure. In the 60+ years of human spaceflight, 21 unfortunate fatalities alongside numerous near-death catastrophes have been observed, with most related to spacecraft liftoff and re-entry. Additional inflight incidents including loss of environmental controls and fire have also required immediate emergency response by crewmembers[546].

Of note, the non-fatal medical emergencies observed during spaceflight include trauma in the form of second-degree burns, development of arrhythmias and pneumonitis, as well as urosepsis. Numerous potential emergent medical conditions have also been suggested for LDEMs, including those associated with environmental (severe galactic radiation exposure such as in a solar particle event[547]), traumatic (in the form of chemical and electrical burns, hemorrhage, fracture), and infectious (sepsis) etiologies. Resultingly, numerous pre- and inflight protocols have been constructed to mitigate in-flight emergent scenarios with relatively robust success[546].

While standard advanced life support protocols have been validated in microgravity, constraints of medical kits available during LDEMs will ultimately limit what interventions can be performed during medical emergencies[548]. With these inherent limitations, researchers have suggested the inclusion of a broadly trained, surgical specialist with the innate ability to problem solve and improvise in spaceflight[549]. Importantly, both decompression sickness[550] (RTDC, LOCL) and trauma-related hypovolemic shock[551] (LOCL) were predicted as conditions likely to occur during the proposed DRM. Resultingly, AI tools relevant to these conditions have been categorized under the umbrella of trauma and emergency medicine and are ultimately detailed here (**Table 11**).

### *10.1 Critical Care Triage*

Tools for accurate patient triage in emergency departments (EDs) exist, such as the ML-based E-triage[552], LR models for both blunt and penetrating wound patients[553], or a more robust deep NN with improved prediction accuracy[554]. ML models were also trained to predict critical vital sign development 1-hour in advance using clinical data from over 40,000 intensive care unit (ICU) patients[555]. Furthermore, Kang et al. trained feedforward NNs on emergency medical service data to predict the need for future critical care, achieving a robust AUC for critical care prediction of 0.867[556]. The CatBoost Python ML framework was even trained for assistive triage of ED patients using EHR data, identifying features associated with increased mis-triage risk while achieving a classification AUC of 0.875 ± 0.006[557]. In the unfortunate circumstance of traumatic injury to multiple crew members during a LDEM, the CMO or crewmember will ultimately be tasked with dividing resources appropriately. Overall mission success will be determined by the CMO's ability to triage those crewmembers in need of emergent critical care quickly and accurately. AI-driven systems that can autonomously triage multiple crewmembers simultaneously and assist in this process would increase probability of mission success.

### *10.2 Shock and Transfusion*

There are multiple tools for accurate detection of shock[558, 559] and need for intervention, including massive transfusion as a therapy[560, 561, 562]. Of note, the Trauma Triage, Treatment, and Training Decision Support (4TDS) supervised ML model, based on a LR framework, was developed for early shock detection. 4TDS achieved a sensitivity, specificity, and AUC of 78.6%, 93.1%, and 0.86, respectively, in prospective validation testing[563]. Additionally, vital signs, laboratory parameters, and non-invasive examination parameters from 1371 trauma patients were used to train a red blood cell demand prediction model. For all prediction parameters, the XGBoost model achieved the greatest AUC of 0.94[564]. Lammers et al. also developed a massive transfusion model for the setting of military trauma by training supervised ML models on demographic, vital sign, and clinical measurement data including need for intubation and administration of tranexamic acid during resuscitation. While all models reported a greater than 90% accuracy in early validation testing, the RF algorithm outperformed during alternative testing[565]. Models that can accurately assess the need for intervention in the setting of cardiogenic shock may be the difference between mission success and LOCL and therefore warrant further investigation.

### *10.3 Emergency Clinical Decision Support Systems*

CDSSs in the setting of medical emergencies were underrepresented in the literature search. Of note, Wang et al. developed an automated emergency CDSS using the knowledge-based tree decoding (K-BTD) method consisting of a knowledge encoder (CNN with self-attention layer), clinical notes encoder (RNN, LSTM, GRU, or BERT), judge net (GRU with an attention layer), and fusion net (weighted sum with attention layer) with training on unstructured clinical notes. The K-BTD model with BERT clinical notes encoder framework outperformed all other models examined[566]. Furthermore, Lang et al. utilized ML to identify the minimal number of clinical guidelines required to reduce 7-day mortality in patients who experience hemorrhagic shock and traumatic brain injury, with LASSO ML model identifying 13 recommendation features[567]. An intelligent video surveillance system model for active monitoring and assistive diagnosis of critical care patients in EDs was proposed[568]. While understudied, these active surveillance models would reduce the need for constant attention to critical crewmembers and allow a CMO to better distribute health care resources in the setting of multi-member traumatic injury.

*10.4 Cardiogenic Ultrasound and Emergency Radiography*

Several AI-powered echocardiography tools were recently reviewed. Importantly, a review by Akkus et al. highlighted those tools for the automated analysis of echocardiograms, including commercial software packages for measurement of ejection fraction, left ventricular and atrial volumes, strain, and coronary heart disease[569]. Additionally, continuous cardiac ultrasound monitoring using GE HealthCare™ devices have been examined for the automated measurement of left ventricular outflow tract velocity time integral (LVOT-VTI), cardiac output (CO)[570], and other hemodynamic measurements[571]. AI-powered tools for emergency radiography are detailed in other sections throughout this manuscript. Of critical relevance, the deep learning algorithm known as Lunit INSIGHT for Chest Radiography was examined for the automatic classification of emergent medical conditions using chest radiographs[572]. Furthermore, Liu et al. highlighted assistive emergency radiology tools based on ANN and CNN frameworks for the diagnosis of abdominopelvic pathologies including diseases of the digestive tract, trauma related pathologies, as well as abdominal aortic aneurysms[573].

*10.5 Prognosis and Outcomes Prediction Models*

Tools to predict prognosis and outcomes following traumatic injuries were surveyed[574, 575, 576, 577, 578, 579]. Several models to predict survival[580] or mortality[581, 582, 583] in trauma patients have also been described. An ensemble ML framework known as SuperLearner was deployed to identify risk and patient-specific modifiable factors following traumatic injury. The model accurately predicted need for transfusion, multi-organ failure, ARDS, venous thromboembolism, and death with robust AUCs of 0.87-0.90, 0.84-0.90, 0.84-0.89, 0.73-0.83, and 0.94-0.97, respectively[584]. Additionally, an interpretable AI smartphone tool known as the Trauma Outcome Predictor (TOP) deploys Optimal Classification Tree models to predict in-hospital mortality and complications for critical care patients. TOP accurately predicted mortality for both blunt and penetrating injuries with a validation c-statistic of 0.884 and 0.941, respectively[585]. Models to accurately predict prognosis in the setting of severe trauma impact astronaut care by helping estimate resources required for treatment. Similarly, CDSSs for emergent medical conditions are critical for LDEMs as prompt care and intervention may be the difference between overall mission success and risk for LOCL.

**D. DISCUSSION**

Given the projected evolution of exploration missions from the moon to Mars by both NASA and commercial entities, the use of robust AI-assisted or stand-alone CDSSs will be critical for the health and safety of astronauts. Numerous AI tools were examined in this survey, but the inventory ultimately uncovered gaps that will ideally be filled prior to projected launch of the Martian missions, with an opportunity for real-world validation during the crewed Artemis missions. This survey noted a dearth of tools specific to the management and treatment of complex or acute diseases, which will be vital to the evolution of medical primacy from terrestrial to space-based assets in exploration missions. Further, most of the referenced tools are intended to assist a board-certified physician for initial triage or clinical diagnosis, who will then deliver the proper treatment and care based on their training in terrestrial medicine. This will not necessarily be the case in spaceflight, as the CMO present may require significantly more support from the computerized medical system in diagnosis and treatment of crewmembers than the typical terrestrial clinician working within a hospital system.

Computers designed for the Orion capsule as part of the Artemis Lunar missions feature speeds and memory capacity 20,000 and 128,000 times those systems used during the 1970s Apollo missions[586]. For reference, a single Dell PowerEdge server put in operation for the Artemis missions for real-time, on-board data analysis features 16,000 times the RAM (64MB) of the entire computing power used in the 1970 Apollo missions (4KB)[587]. Similarly, Orion will reportedly have compute speeds 20,000 times that of the ISS systems[588]. Mission specific CDSS will likely be constructed based upon those medical conditions suggested by PRA tools like the IMPACT suite for a given DRM of interest. IMPACT applies NASA's real world evidence library to mission- and crew-specific features to make trades based on diagnostic and treatment capabilities for the desired outcome metric or mass/volume constraints. Akin to the evidence-based determination of what should be included within the onboard "medical backpack", a similar trade-space assessment will likely extend to creation of pre-flight CMO curricula, and the curation of a mission-specific CDSS. Here, system compute and storage needs, as well as selection of pre-trained architectures and data libraries, will be weighed against overall mission risk and the medical conditions that are predicted to occur (**Figure 4**).

Limitations to the implementation of AI tools are far outweighed by the anticipated benefits. However, the most significant barrier includes lack of external and real-world validation testing of the identified AI agents, which could potentially be easily satisfied during lunar exploration missions in the pursuit of Earth-independent medical operations. The tools will therefore have the opportunity to evolve during the Moon to Mars effort of space exploration missions. Additionally, although modern computing systems are physically compact, there will be constraints on the interface between end-user and a CDSS on extraterrestrial missions based on mass and volume restrictions of the vehicle. Medical systems used for exploration class missions must also be equipped with radiation-protective attributes given longer projected exposure time. AI assistive tools for diagnosis and treatment will be required for successful missions in the future, and space medicine as a field must prioritize addressing the current gaps and limitations of existing software and hardware to provide optimal care for the astronaut corps.

The focus of research and development of AI tools for eventual Mars exploration will need to address communication delays impeding terrestrial ground support, limitations in replenishing consumable or damaged physical supplies and the near impossibility of urgent evacuation of crewmembers. Tools used to optimize medical care in the Lunar and Martian environments will require extensive validation and reliability testing on Earth through prospective trials before future deployment on LDEMs. Ultimately, mission success is dependent, first and foremost, on crew health and performance. AI models such as those highlighted here may be the basis of future CDSS that will help manage the myriad medical conditions that may arise during long duration exploration spaceflight. If cultivated appropriately, this system would also extend to include both pre- and post-mission care, in addition to intra-mission preventive efforts, for the most comprehensive management of astronaut health and performance. The immense progress in the field of medical AI over the last decade should by no means be understated and new tools and devices will undoubtedly be available for the next generation of space exploration. Prioritizing the unique needs of the spaceflight environment will be critical as stakeholders create new iterations of existing products or develop novel resources that could be utilized by CMOs and crewmembers. It is undeniable that AI tools will be essential for deep space exploration missions of the future to be conducted safely and successfully.

## E. CONCLUSION

Numerous AI-driven models relevant to the ten systems-based categories including general diagnostic tools, tools to diagnose and manage respiratory, dermatologic, neurologic, auditory and vestibular, ophthalmic, musculoskeletal, infection-associated, and gynecologic conditions, as well as tools that could be deployed in the setting of trauma and emergency, were highlighted in this extensive literature survey (**Figure 5**). Uncertainties regarding the development of a next-generation spaceflight CDSS still remain but the field of aerospace medicine anticipates a transformative improvement in medical care of astronauts with the incorporation of AI technologies. Ultimately, engineers and clinicians must work together to integrate these clinical support systems within the compute and connectivity constraints that will exist in the spacecraft of future exploration missions.

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**CONFLICT OF INTEREST**

The authors declare that they have no competing financial interests that could have appeared to influence the work reported.

**DATA AVAILABILITY**

No original data was generated or presented within this manuscript. Available data sets can be found in the original publications referenced.

**FIGURE LEGENDS**

**Figure 1: Medical conditions highlighted by IMPACT for the proposed extended duration Artemis mission.** Medical conditions predicted to be most likely based on frequency as well as associated with task time lost (TTL), return to definitive care (RTDC), or loss of crew life (LOCL) for the proposed extended duration Artemis DRM are detailed. Additional keywords, phrases, and MeSH terms (associated with each medical condition) utilized in the literature search are presented.

**Figure 2: Schematic representation of literature survey search results and screening methods.** Reference search yielded over 100,000 original articles and reviews. After primary assessment of titles and abstracts, 929 original research articles were identified. Secondary full review of those manuscripts and removal of duplicates identified 567 original research articles and reviews. Removal of articles deemed unsuitable for survey inclusion and addition of original research manuscripts uncovered within review articles identified 469 original research articles (and associated reviews) for final inclusion.

**Figure 3: Graphical representation of the ten systems-based categories used to group the DRM-associated medical conditions.** Images from the following URLs were modified for the creation of this figure using Adobe Illustrator, Photoshop: https://www.freepik.com/premium-psd/space-suits-isolated-white-background-ai-generated_41111886,https://www.clipartmax.com/download/m2i8i8N4b1A0b1b1_medical-logo-medical-cross-symbol-png/,https://www.nasa.gov/sites/default/files/thumbnails/image/as17-147-22526_orig_1.jpg.

**Figure 4: Compute and storage tradespace assessment for future CDSSs.** Much like the figurative "backpack" analogy to determine which medical supplies (each with an associated mass, volume, and measurable "cost") are appropriate for resource limited medical care, future CDSSs will balance compute and storage constraints (GPUs, CPUs, pre-trained datasets) with overall mission risk. Images from the following URLs were modified for creation of this figure using generative fill (Adobe Illustrator) and DALL-E of ChatGPT-4.

**Figure 5: Sunburst hierarchy representing the number of AI-tools applicable to the medical conditions for the proposed extended duration Artemis mission.** Graphical representation highlighting the number of AI-tools referenced for each systems-based category of our survey. The number of articles included within each systems based category is as follows: general diagnostic tools (25), tools to diagnose and manage respiratory (40), dermatologic (34), neurologic (28), auditory and vestibular (30), ophthalmic (34), musculoskeletal (104), infection-associated (92), and gynecologic (19) conditions, as well as tools that could be deployed in the setting of trauma and emergency (34). Image from the following URL was modified for creation of this figure using Adobe Illustrator: https://imgbin.com/png/HjZBT5wX/robot-head-png.

**Figure 1**

| MOST LIKELY CONDITION BASED ON FREQUENCY | |
|---|---|
| **MEDICAL CONDITION** | **ADDITIONAL KEYWORDS/PHRASES** |
| **Lunar Dust Exposure – Surface EVA** | Inhalation, Exposure |
| **Lunar Dust Exposure – EVA Habitat** | Inhalation, Exposure |
| **Insomnia** | Sleep |
| **EVA-Related Suit Contact Injury** | Sore, Pressure Injury, Contact Injury |
| **EVA-Related Paresthesia** | Neuropathy, Peripheral Neuropathy |
| **Headache** | Migraine |
| **Ear/Sinus Barotrauma** | Otolaryngology, Otoscope, Tinnitus, Inner Ear |
| **Spaceflight-Associated Skin Rash** | Dermatology |
| **Eye Irritation/Corneal Abrasion/Ulcer** | Ophthalmology, Ophthalmic, Ocular |
| **Skin Abrasion** | Dermatology |
| **MOST LIKELY CONDITION TO CAUSE TASK TIME LOST (TTL)** | |
| **MEDICAL CONDITION** | **ADDITIONAL KEYWORDS/PHRASES** |
| **EVA-Related Shoulder Injury** | Musculoskeletal, Impingement, Ultrasound, X-ray, Radiograph, Muscle Strain |
| **Upper Extremity Sprain** | Tennis Elbow, Biceps, Triceps |
| **Lower Extremity Sprain** | Quadriceps, Hamstring, Calf, Achilles, Knee |
| **Ear/Sinus Barotrauma** | Otolaryngology, Otoscope, Tinnitus, Inner Ear |
| **Spaceflight-Associated Skin Rash** | Dermatology |
| **Back Spain** | Spine |
| **EVA-Related Suit Contact Injury** | Sore, Pressure Injury, Contact Injury |
| **Insomnia** | Sleep |
| **Neck Sprain** | Whiplash, Spine, Cervical |
| **Acute Diarrhea** | Gastrointestinal, Gastroenteritis |
| **MOST LIKELY CONDITION TO CAUSE RETURN TO DEFINITIVE CARE (RTDC)** | |
| **MEDICAL CONDITION** | **ADDITIONAL KEYWORDS/PHRASES** |
| **Wrist Fracture** | |
| **Foreign Body in Eye** | Ophthalmology, Ophthalmic, Ocular |
| **EVA-Related Decompression Sickness** | |
| **Eye Irritation/Corneal Abrasion/Ulcer** | Ophthalmology, Ophthalmic, Ocular |
| **Chemical Eye Burn** | Ophthalmology, Ophthalmic, Ocular |
| **Risk for Pregnancy** | |
| **Ear/Sinus Barotrauma** | Otolaryngology, Otoscope, Tinnitus, Inner Ear |
| **Pregnancy** | |
| **Bacteria Skin and Soft Tissue Infection** | Cellulitis, Folliculitis, Necrotizing Fasciitis |
| **Acute Diarrhea** | Gastrointestinal, Gastroenteritis |
| **MOST LIKELY CONDITION TO CAUSE LOSS OF CREW LIFE (LOCL)** | |
| **MEDICAL CONDITION** | **ADDITIONAL KEYWORDS/PHRASES** |
| **EVA-Related Decompression Sickness** | |
| **Respiratory Failure** | Acute Respiratory Distress Syndrome, ARDS |
| **Urinary Tract Infection** | Urology |
| **Trauma-Related Hypovolemic Shock** | |
| **Abnormal Uterine Bleeding** | Polyp, Adenomyosis, Leiomyoma, Coagulopathy |
| **Ebullism** | |
| **Bacterial Skin and Soft Tissue Infection** | Cellulitis, Folliculitis, Necrotizing Fasciitis |
| **Obstructed Airway** | |
| **Toxic Inhalation of Combustion Products** | |
| **Dental Abscess** | Molar, Cavity |

**Figure 2**

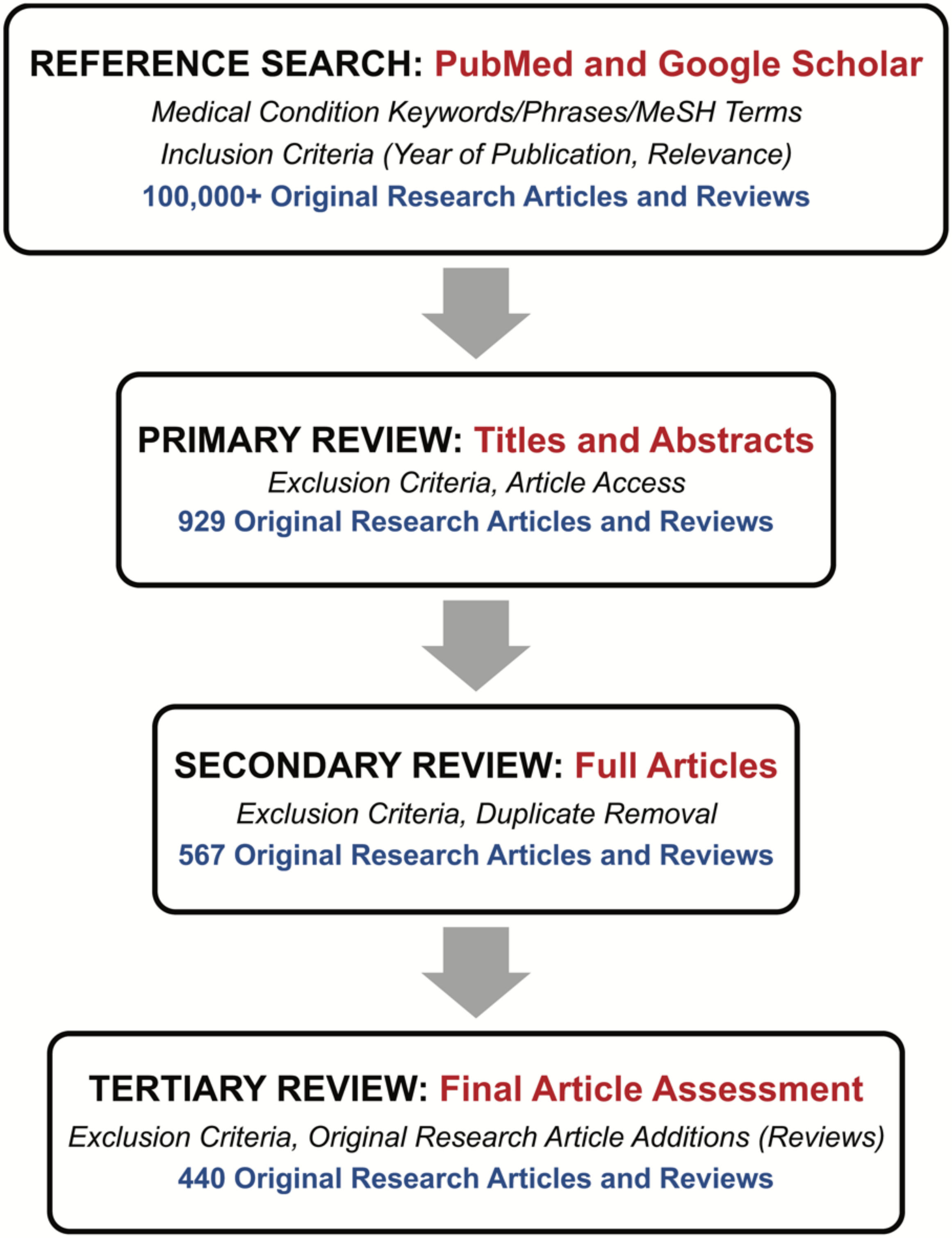
REFERENCE SEARCH: PubMed and Google Scholar
Medical Condition Keywords/Phrases/MeSH Terms
Inclusion Criteria (Year of Publication, Relevance)
100,000+ Original Research Articles and Reviews
PRIMARY REVIEW: Titles and Abstracts
Exclusion Criteria, Article Access
929 Original Research Articles and Reviews
SECONDARY REVIEW: Full Articles
Exclusion Criteria, Duplicate Removal
567 Original Research Articles and Reviews
TERTIARY REVIEW: Final Article Assessment
Exclusion Criteria, Original Research Article Additions (Reviews)
440 Original Research Articles and Reviews

**Figure 3**


NEUROLOGIC
AUDITORY AND VESTIBULAR
OPHTHALMIC
TRAUMA AND EMERGENCY
GENERAL DIAGNOSTIC SYSTEMS
RESPIRATORY
DERMATOLOGIC
INFECTION-ASSOCIATED
MEDICAL CONDITIONS
MUSCULOSKELETAL
GYNECOLOGIC

**Figure 4**

**Figure 5**

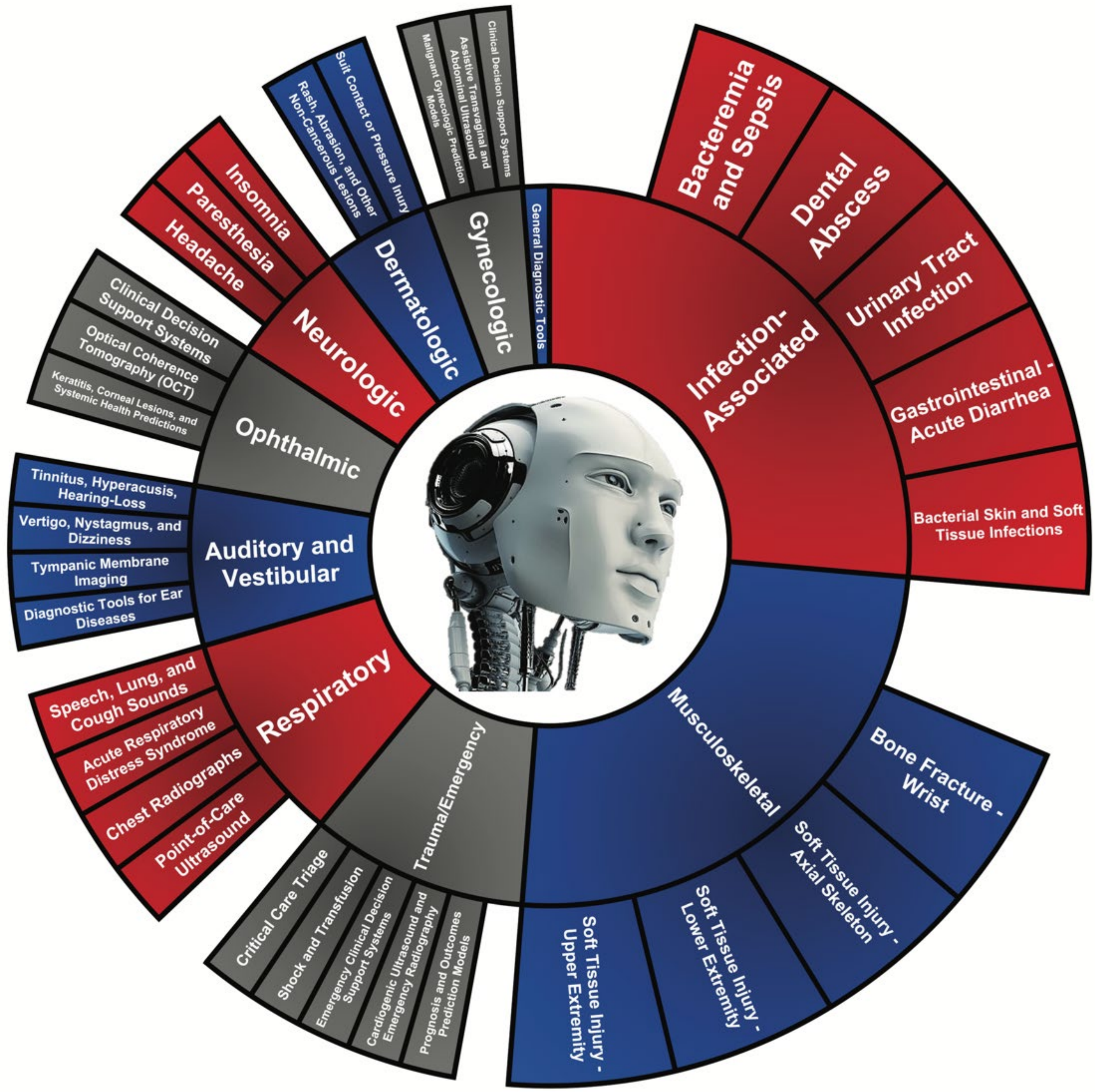
Infection-Associated
Bacteremia and Sepsis
Dental Abscess
Urinary Tract Infection
Gastrointestinal - Acute Diarrhea
Bacterial Skin and Soft Tissue Infections
Musculoskeletal
Bone Fracture - Wrist
Soft Tissue Injury - Axial Skeleton
Soft Tissue Injury - Lower Extremity
Soft Tissue Injury - Upper Extremity
Trauma/Emergency
Critical Care Triage
Shock and Transfusion
Emergency Clinical Decision Support Systems
Cardiogenic Ultrasound and Emergency Radiography
Prognosis and Outcomes Prediction Models
Respiratory
Speech, Lung, and Cough Sounds
Acute Respiratory Distress Syndrome
Chest Radiographs
Point-of-Care Ultrasound
Auditory and Vestibular
Tinnitus, Hyperacusis, Hearing-Loss
Vertigo, Nystagmus, and Dizziness
Tympanic Membrane Imaging
Diagnostic Tools for Ear Diseases
Ophthalmic
Clinical Decision Support Systems
Optical Coherence Tomography (OCT)
Keratitis, Corneal Lesions, and Systemic Health Predictions
Neurologic
Insomnia
Paresthesia
Headache
Dermatologic
Rash, Abrasion, and Other Non-Cancerous Lesions
Suit Contact or Pressure Inury
Gynecologic
Malignant Gynecologic Prediction Models
Assistive Transvaginal and Abdominal Ultrasound
Clinical Decision Support Systems
General Diagnostic Tools

**TABLE LEGENDS**

**Table 1:** Overview of those AI models commonly deployed in terrestrial medicine and referenced throughout manuscript.

**Table 2:** Most relevant general diagnostic AI-tools including their application descriptor, framework, and relevance to the proposed extended duration Artemis space exploration mission, where applicable.

**Table 3:** Most relevant respiratory AI-tools including their application descriptor, framework, and relevance to the proposed extended duration Artemis space exploration mission, where applicable.

**Table 4:** Most relevant dermatologic AI-tools including their application descriptor, framework, and relevance to the proposed extended duration Artemis space exploration mission, where applicable.

**Table 5:** Most relevant neurologic AI-tools including their application descriptor, framework, and relevance to the proposed extended duration Artemis space exploration mission, where applicable.

**Table 6:** Most relevant auditory and vestibular AI-tools including their application descriptor, framework, and relevance to the proposed extended duration Artemis space exploration mission, where applicable.

**Table 7:** Most relevant ophthalmic AI-tools including their application descriptor, framework, and relevance to the proposed extended duration Artemis space exploration mission, where applicable.

**Table 8:** Most relevant musculoskeletal AI-tools including their application descriptor, framework, and relevance to the proposed extended duration Artemis space exploration mission, where applicable.

**Table 9:** Most relevant infection-associated AI-tools including their application descriptor, framework, and relevance to the proposed extended duration Artemis space exploration mission, where applicable.

**Table 10:** Most relevant gynecologic AI-tools including their application descriptor, framework, and relevance to the proposed extended duration Artemis space exploration mission, where applicable.

**Table 11:** Most relevant trauma and emergency AI-tools including their application descriptor, framework, and relevance to the proposed extended duration Artemis space exploration mission, where applicable.

**TABLE 1**

| MODEL | DESCRIPTION | USE CASE IN MEDICINE |
|---|---|---|
| Machine Learning (ML)[6] | Identification of patterns or trends within data through learning based on sample datasets | Analysis of electronic medical record (EMR) and expansive numeric datasets |
| Convolution Neural Network (CNN)[7] | Deep learning model to identify spatial features from datasets (such as images) containing a grid pattern | Medical image analysis |
| Recurrent Neural Network (RNN)[8, 9, 10] | Deep learning technique which utilizes non-linear yet interconnected, bi-directional networks for classification of sequence-based inputs | Medical time series data analysis |
| Artificial Neural Network (ANN or NN)[11, 12] | Nodes or neurons (organized in layers) performing a prespecified task for the generation of an output | Prediction within numeric or imaging medical datasets |
| Generative Adversarial Network (GAN)[13] | Characterized by their inherent ability to extract features from images through distribution learning | Medical image analysis |
| Natural Language Processing (NLP)[14, 15] | Modeling human language through machine learning approaches | Analysis of medical literature, patient records, medical notes, or any form of natural language text |
| Transformers[16, 17] | Advancement in deep learning architecture consisting of deeply stacked self-attention layers which can differentially weigh inputted data, necessary for the human-like capabilities of next-generation large language models (LLMs) | NLP tasks in addition to medical image analysis |

**TABLE 2**

| REFERENCE | APPLICATION | AI FRAMEWORK | RELEVANCE |
|---|---|---|---|
| Tootooni et al. 2019[52] | CCMapper | NLP | Chief complaint mapping tool with high level of agreement to board-certified physicians |
| Hammoud et al. 2022[58] | Avey | Bayesian Models | General diagnostic algorithm tested on over 400 clinical vignettes |
| Zakka et al. 2023[66] | Almanac | LLMs | Pre-trained large medical language model compared to ChatGPT for differential diagnosis and treatment recommendations |
| Li et al. 2023[67] | ChatDoctor | Meta-AI LLaMA | Use of both online and offline medical databases alongside ability to assess patient needs more accurately through real-world dialogue |

**TABLE 3**

| REFERENCE | APPLICATION | AI FRAMEWORK | RELEVANCE |
| --- | --- | --- | --- |
| Vatanparvar et al. 2021[83] | SpeechSpiro | CNN-LSTM | Determines lung functional parameters from 60 second audio recordings |
| Kvapilova et al. 2020[93] | Healthmode | CNNs | Continual cough collection through cellular device internal microphone |
| Kim et al 2019[101] | FAST-PACE | RNN-LSTM | Prediction of respiratory failure up to 6-hours in advance using only basic vital sign data |
| Pellegrini et al. 2023[118] | Xplainer | Vision-Language Models | Automated chest radiograph analyzer using a zero-shot approach highlighted importance of descriptive inputs for improve diagnostic accuracy |

**TABLE 4**

| REFERENCE | APPLICATION | AI FRAMEWORK | RELEVANCE |
| --- | --- | --- | --- |
| Fergus et al. 2022[141] | | Faster Region-CNN | Classification of pressure ulcer using smartphone-captured digital images |
| Dulmage et al. 2021[150] | VisualDx DermExpert | CNNs | Large image training set to produce a robust diagnostic accuracy, outperforming clinicians |
| Escalé-Besa et al. 2023[160] | Autoderm | NNs | Ability to diagnose skin lesions for up to 44 dermatologic disorders with images capture from a smartphone |
| Zhou and Gao 2023[161] | SkinGPT | Vision- and Q-Transformers, LLMs | Interactive dialogue machine provides better user experience when providing dermatologic diagnosis |

**TABLE 5**

| REFERENCE | APPLICATION | AI FRAMEWORK | RELEVANCE |
|---|---|---|---|
| Sharma et al. 2021[184] | | Supervised ML | Accurate diagnosis of six common sleep disorders using EEG signals |
| Philip et al. 2020[188] | KANOPEE | Decision Tree Machine Learning | Virtual screening agent that provides sleep and behavioral advice |
| Faeghi et al. 2021[193] | | SVM | Computer-aided diagnosis of Carpal Tunnel Syndrome using B-mode ultrasound images |
| Chaix et al. 2022[202] | VikMigraine Chatbot | ML and NLP | Prospective evaluation of headache chatbot on over 600 patients |

**TABLE 6**

| REFERENCE | APPLICATION | AI FRAMEWORK | RELEVANCE |
|---|---|---|---|
| Elbasi et al. 2018[222] | | Pruned Tree J48, Random Forest | Accurate diagnosis of hearing loss using audiometric data |
| Reinhardt et al. 2022[236] | VertiGo-App | ML | Smartphone application using front and rear cameras for nystagmus detection |
| Binol et al. 2022[244] | OtoXNet | ResNet-v2 and Random Forest | Automated diagnosis of three tympanic membrane diseases using otoscopy videos |
| Wijaya et al. 2023[251] | | CNN | Smartphone application for diagnosis of 20 middle ear diseases using otoendoscopy images |

**TABLE 7**

| REFERENCE | APPLICATION | AI FRAMEWORK | RELEVANCE |
|---|---|---|---|
| Chen et al. 2023[262] | EE-Explorer | DenseNet201, XGBoost, InceptionV3 | Metadata combined with smartphone ocular surface images for diagnosis of corneal diseases and ocular trauma |
| Wen et al. 2022[271] | LLCT | CNN w/ self attention transformer | OCT image classification for ophthalmic disorders |
| Zhang et al. 2022[278] | KeratitisNet | ResNext101_32x16d and DenseNet169 | Diagnosis of bacterial, fungal, or parasitic infectious keratitis from slit-lamp images |
| Zhang et al. 2020[286] | | ML TensorFlow, InceptionV3 | Retinal fundus images to classify patient health parameters such as hypertension |

**TABLE 8**

| REFERENCE | APPLICATION | AI FRAMEWORK | RELEVANCE |
|---|---|---|---|
| Lee et al. 2021[306] | SMART-CA | CNN | Accurate diagnosis of rotator cuff injury using ultrasound imaging |
| Wang et al. 2023[334] | | Random Forest-based SVM | Accurate diagnosis of achilles tendinopathy using ultrasound images |
| Barreveld et al. 2023[371] | PainDrainer | | AI-based digital application for the self-management of neck and back pain |
| Raisuddin et al. 2021[403] | DeepWrist | Deep Learning | Accurate wrist fracture diagnosis model deployed on a challenge set consisting of fracture radiographs that required a confirmatory CT scan |

**TABLE 9**

| REFERENCE | APPLICATION | AI FRAMEWORK | RELEVANCE |
|---|---|---|---|
| Yanagisawa et al. 2023[433] | | DeepLabv3, InceptionV3 CNN | Diagnosis of common skin disorders including bacterial skin infection using non-standard, original images |
| Sanaeifar et al. 2022[443] | DxGenerator | NLP, MetaMap | Gastrointestinal differential diagnosis generator for over 120 diseases with the common symptom of abdominal pain |
| Brenton et al. 2020[464] | APAS® Independence | | Automated interpretation of urinary cultures with clinical validation testing |
| Hossain et al. 2023[482] | CaViT | Vision Transformer Model | Prediction of dental caries using smartphone images |
| Mao et al. 2018[500] | | Gradient Boosted ML | Prediction of sepsis using 6 basic vital signs |

**TABLE 10**

| REFERENCE | APPLICATION | AI FRAMEWORK | RELEVANCE |
|---|---|---|---|
| Ahmad et al. 2020[531] | | MLP | Accurate diagnosis of numerous gynecologic disorders using a 54-input questionnaire |
| Huo et al. 2023[536] | | Deep CNN | Transabdominal and transvaginal ultrasound images for automated detection of uterine fibroids |
| Lai et al. 2023[545] | | XGBoost and Random Forest Ensemble | CDSS to predict risk of non-benign postmenopausal endometrial lesions |

**TABLE 11**

| REFERENCE | APPLICATION | AI FRAMEWORK | RELEVANCE |
| --- | --- | --- | --- |
| Levin et al. 2018[552] | E-triage | Random Forest ML | Emergency department triage tool using easily accessible patient data |
| Pinevich et al. 2022[563] | 4TDS | Logistic Regression ML | Prospective evaluation of an early shock detection model |
| Wang et al. 2021[566] | | K-BTD with BERT | Emergency CDSS reported robust accuracy when evaluated on top 100 ICD codes |
| Hwang et al. 2019[572] | Lunit INSIGHT for Chest Radiography | Deep Learning | Commercially available and automated chest radiograph analyzer for normal and abnormal classification |
| El Hechi et al. 2022[585] | Trauma Outcome Predictor (TOP) | Optimal Classification Tree Models | Interpretable AI-smartphone application to predict mortality and complication risk for patients with penetrating and blunt trauma wound injuries |

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