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THE ROLE OF ARTIFICIAL INTELLIGENCE IN SPACE MEDICINE

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ABSTRACT

Space is considered to be the most inhospitable environment known to man. A lack of oxygen, microgravity, extremes of temperature, ionising radiation and the inability to grow food being only a few of the challenges that space exploration may pose to those brave enough to travel there.[1] Consequently, astronauts encountered numerous health risks primarily due to the effects of microgravity and ionising radiation as well as the psychological impacts of isolation and confinement.[2,3] Because of this, it is imperative that the health and wellbeing of astronauts be monitored closely to ensure their safety. This is currently achieved via telemedicine, in which medical personnel on earth communicate with those in space. However, this is not without limitations such as the inability to physically examine those in space and communication delays that may be encountered due to the vast transmission distances. In the case that communications become compromised or infeasible, astronauts may be left vulnerable to a wide range of potential health complications. Therefore, a redundancy solution to monitor astronaut health alongside direct astronaut-to-earth communication is required. This could be achieved via the use of artificial intelligence (AI). AI allows for the health of astronauts to be automatically monitored and provides an effective solution to some of the biological and psychological issues that astronauts encounter. This essay explores the role of AI in a selection of health issues encountered by astronauts.

TELEMEDICINE IN SPACE

Almost every physiological system in the human body can be affected by space travel, often resulting in hypotension, tachycardia, fluid redistribution, optic disc oedema, dysrhythmias, cardiac remodelling, kidney stones, muscle atrophy, bone resorption, carotid intima thickening and long-term risks of cancer.[1,3,4] In addition to this, astronauts also experience significant psychological stress due to isolation, confinement and a complex work environment.[2,5] Currently, astronauts are monitored from Earth using telemedicine which grants medical personnel the ability to monitor and manage astronaut health from a distance. This generally involves monitoring vital signs such as heart rate, respiratory rate, blood pressure, temperature, and ECG findings alongside diagnostic imaging in the form of ultrasound which are all transmitted to Earth for interpretation. However, as previously mentioned, telemedicine is limited by its inability to perform physical examinations or intervention. A further issue with telemedicine relates to the difficulties encountered with deep space communication. Communication between astronauts and Earth generally requires transmissions to be sent over very large distances. While transmissions generally travel at the speed of light (~300,000km/s), communication latency becomes a significant challenge as the distance between transmitters and receivers increases. For example, the average distance between Earth and the Moon is approximately 384,000km which results in minimal transmission latency of ~1.3 seconds. However, this becomes far more significant when considering that the distance between Earth and Mars is anywhere between 55,000,000 - 378,000,000km resulting in a transmission latency between 3 - 21 minutes.[6] Furthermore, there is also risk of damage to transmission relay satellites due to space debris or cosmic radiation. Such communication challenges highlight the need for a redundancy measure in place to monitor the health of astronauts if direct communication became unavailable or ineffective. This is particularly relevant in the current day with the intention to send astronauts to Mars and beyond.

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ARTIFICIAL INTELLIGENCE

The utilisation of AI provides an effective and innovative way to overcome the challenges associated with telemedicine in space. This powerful tool could allow for the effective monitoring of astronauts, in addition to acting as a redundancy measure in the case that communications become compromised. AI refers to mathematical algorithms that mimic human intelligence with capabilities such as learning, adaptation, reasoning, and sensory interaction.[7] It functions by analysing large datasets, extracting important features and using those features to extrapolate new data and formulate accurate predictions or classifications. The introduction of this technology has resulted in a paradigm shift in the way we analyse complex data and has proven to be a powerful problem-solving tool.[8,9] Deep learning is one of the most rapidly growing subfields of AI. This utilises algorithms called neural networks that are designed to mimic the architecture and function of the brain.[10] In the past, AI was limited to working with simple, tabular data, however, with the rise of deep learning, AI is now able to learn from complex, natural data such as images and sequences. In the field of medicine, there are already numerous clinically approved AI systems with successful application in stroke diagnosis, diabetic retinopathy screening, ECG analysis and MRI interpretation.[11] Given the complexity of aerospace medicine and the significant challenges in providing healthcare to astronauts, there is an opportunity for AI to play a significant role in delivering healthcare to astronauts as they venture further and further from the earth.

MONITORING VITAL SIGNS

The effects of microgravity and space travel result in physiological dysfunction across almost every body system. Therefore, it is crucial to monitor these systems to identify abnormalities, manage them accordingly and prevent complications that could compromise the mission or even be life-threatening. The most fundamental and critical vital signs to monitor are heart rate, blood pressure, respiratory rate, oxygen saturation and temperature. These can be measured via the use of blood pressure cuffs, pulse oximetry and electrocardiograms (ECG) or with innovative wearable technology that allows vital signs to be measured via a wearable device or a piece of clothing with integrated monitoring.[12,13] This continuous stream of numerical data provides an excellent opportunity for AI-integrated monitoring of astronaut health. It is well documented that microgravity causes significant cardiovascular dysfunction resulting in hypotension, tachycardia and risk of arrhythmias; all of which be identified with the aforementioned monitoring.[14] A simple computational program would be effective at identifying when numerical values become abnormal, however, a more complex system is required to analyse ECG waveform morphology to identify cardiac dysrhythmias. Microgravity infers an increased risk of cardiac arrhythmias which has presented in previous studies as premature ventricular contractions, atrial fibrillation, non-sustained ventricular tachycardia and QTc prolongation.[15–17] Continuous ECG monitoring by an AI could be highly effective at identifying and classifying cardiac arrhythmias. Numerous studies have developed AI systems that can classify arrhythmias with exceptional accuracy.[18–22] This illustrates the potential effectiveness of implementing AI systems for the continuous monitoring of astronaut vital signs and ECG interpretation during space-travel.

ULTRASOUND DIAGNOSTICS

Currently, ultrasound (US) is the only feasible modality of diagnostic imaging in space due to its portable nature compared to computed tomography (CT) or magnetic resonance imaging (MRI). US is particularly useful in space due to issues related to microgravity. Microgravity has a profound effect on the cardiovascular system causing a decrease in circulating blood volume leading to fluid redistribution, hypotension and subsequent cardiac remodelling.[23] This remodelling can result in a significant reduction in physical capacity upon returning to partial gravity (i.e. the Moon or Mars) or full gravity when returning to Earth.[24] AI can allow for monitoring of such cardiac dysfunction through the automated interpretation of ultrasound echocardiography. Previous studies have utilised AI models to correctly identify and interpret cardiac dysfunction on echocardiography such as abnormal left ventricular volumes, ejection fraction and myocardial wall motion with high accuracy.[25–29] This identification could allow for appropriate measures to be taken to optimise the physical capabilities of astronauts who experience this issue.

Another complication of microgravity is the predisposition to kidney stones due to bone breakdown and urine calcium supersaturation.[30] This can escalate to a medical emergency if left untreated due to significant pain and infection risk with a very challenging prospect of evacuation from space. Luckily, many of these events occur shortly after returning to Earth, however, in 1982 a Russian cosmonaut narrowly missed being medically evacuated during a mission due to kidney stones.[31,32] Modern AI systems have the capability of kidney stone diagnosis from US images as well as determining stone composition (i.e. calcium, urate); however, management in space remains a limitation with the optimal treatment being prevention.[33–35]

The risk of trauma during space travel is another risk that is practically impossible to completely remove and may require urgent diagnostics to ascertain if emergency management is required. US is highly effective at identifying abdominal trauma with the FAST (Focused Assessment with Sonography for Trauma) scan which is utilised around hospitals internationally to identify any bleeding or fluid in the abdomen. Further utilisation of AI may include the automated interpretation of FAST scans in space. Previous clinical trials have already illustrated that a deep learning

algorithm can rapidly interpret FAST scans (in both adult and paediatric populations) with sensitivity and specificity between 90 - 100%.[36,37] There has been a previous case report of ocular trauma on the ISS requiring ocular ultrasound for diagnostic purposes.[38] This is yet another potential role of AI as Chen and colleagues developed a deep learning model to automatically diagnose abnormalities on ophthalmic ultrasound.[39] In future years, there will likely be many imaging modalities available such as portable MRI machines or entirely new imaging techniques that can be applied in the domain of space travel and would allow even further expansion of the capabilities of AI-guided image diagnostics.

PSYCHOLOGICAL STRESS

Astronauts experience significant psychological stress due to prolonged isolation with a small group of individuals, confinement, and the risk of little to no possibility of rescue in an emergency. This is further complicated by circadian dysfunction and poor sleep quality due to microgravity and 90-minute periods between sunrise and sunset on the ISS.[1] This can manifest as psychiatric disorders such as depression, anxiety and adjustment disorders which can impair an astronaut's technical and cognitive performance. There is strong evidence that AI can be utilised to both identify and manage psychological disorders such as depression and anxiety. For example, previous studies have utilised neural networks to identify emotional states and even diagnose depression on facial features alone.[40,41] This approach also been adopted and expanded to diagnose depression based on speech waveforms alone.[42,43] Similar approaches have also been adopted for the identification of other psychiatric issues experienced by astronauts such as anxiety and stress-related disorders.[44] Not only is AI applicable to the diagnosis of psychiatric disease, but it can also play a role in management. There have been several clinical studies of AI chatbots created to deliver psychotherapy (eg. Cognitive behavioural therapy) for the management of depression and anxiety. For example, Fitzpatrick and colleagues developed Woebot, a fully conversational agent designed to deliver cognitive behavioural therapy which has been shown to improve symptoms of depression in a randomised controlled trial.[45] Similar systems have also been trialled which have shown an increase in positive mood and a reduction in anxiety levels.[46,47] In fact, this concept has already been trialled on the ISS with an AI system called CIMON (Crew Interactive Mobile Companion) as a method of relieving psychological stress experienced by astronauts.[48,49]

CONCLUSION

In summary, outer space is an incredibly hostile environment that poses significant health risks to astronauts. These risks are currently managed via the use of telemedicine; however, AI provides a potential alternative and redundancy measure in cases where standard telemedicine becomes unavailable or compromised. AI-based systems have the capability of monitoring astronaut vital signs, analysing ECG waveforms, performing US diagnostics, and even providing psychological support to those who need it. Whilst we are still a long way from generalised AI as seen in science-fiction such as HAL 9000 from 2001: A Space Odyssey or TARS from Interstellar, with technological advancements, astronauts may be sharing space shuttles and exploring outer space with AI to help reduce the psychological and psychological burden of space travel.

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