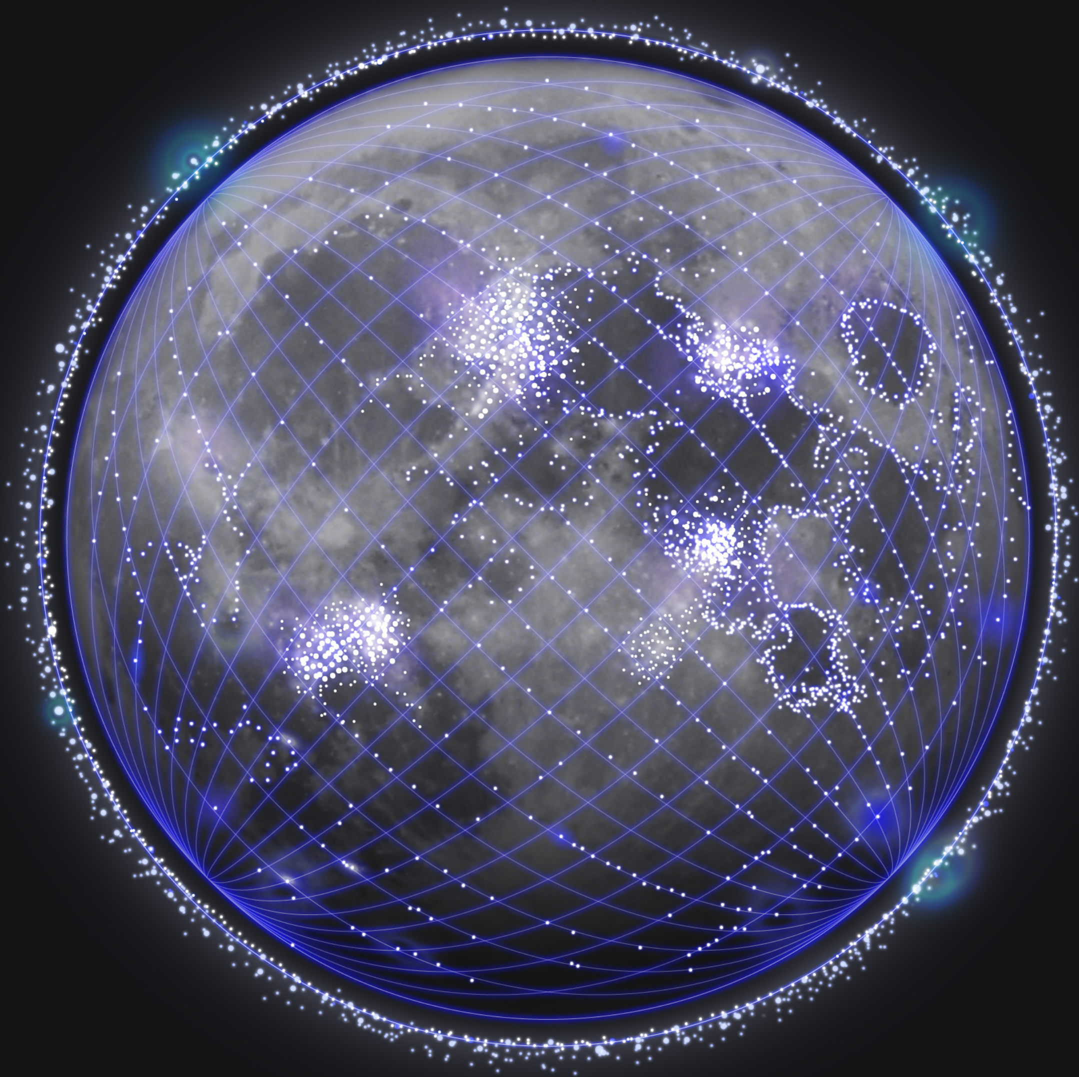
Using Artificial Intelligence and Machine Learning
for Optimizing Space Mission Strategies

TEST CASE: OPTIMIZE LUNAR OUTPOST SPECIFICATIONS



Southern Hemisphere Space Studies Program 2022

REPORT

INTERNATIONAL SPACE UNIVERSITY®

University of South Australia

Using Artificial Intelligence and Machine Learning for Optimizing Space Mission Strategies

TEST CASE: OPTIMIZE LUNAR OUTPOST SPECIFICATIONS

REPORT

Southern Hemisphere Space Studies Program 2022

OUR MISSION

Enabling humanity's exploration of space through an interdisciplinary approach to using artificial intelligence and machine learning for the optimization of a sustainable lunar outpost.

The 2022 Southern Hemisphere Space Studies Program was held by the International Space University (ISU) and the University of South Australia (UniSA).

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The cover depicts a futuristic view of the Moon showing a combination of artificial intelligence data mapping and the Moon overview from the lunar Gateway, with larger settlements and villages established around historic cultural heritage Apollo mission sites.

Moon photograph courtesy of SHSSP22 participant, Ashwini Vaidya.

Artwork courtesy of the SHSSP22 graphic design team.

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ABSTRACT

This study undertakes an interdisciplinary investigation into the application of artificial intelligence and machine learning to optimize the establishment of a lunar outpost. It focuses on seven core disciplines: space applications; engineering; management and business; human performance; science; humanities; and policy, ethics, and law.

A review of existing literature for each discipline informed the selection of target specifications to optimize. These specifications were evaluated, and outpost location optimization was selected as the primary subject of the study. Five selected specifications were identified as needing to be satisfied: maximizing solar exposure; ease of terrain access; proximity to sites of scientific interest; minimizing environmental impacts on crew health; and access to resources.

The report identifies functional requirements that need to be satisfied by an artificial intelligence and machine learning application and develops a final proposed system. It then presents a prototype computational model for optimizing outpost location for terrain access.

A discussion of the ethical, policy and legal implications of the proposed system follows, and future extensions and improvements of the system are recommended, including applications for future off-Earth missions and the commercialization of AI as a service.

FACULTY PREFACE

A permanent and sustainable human outpost on the Moon is the next major step in the expansion of humankind in space. Artificial Intelligence and Machine Learning (AI/ML) can help identify key parameters of such as settlement.

In this Report, the SHSSP22 participants expose how to optimize the location of a lunar outpost while keeping in mind the radiation exposure, terrain access, scientific interest, environmental impact on humans and access to in situ resources. They take an interdisciplinary, international and intercultural approach to address the engineering, business, political and ethical aspects of using AI/ML to build a long-term human settlement on the Moon.

The SHSSP participants have worked with enthusiasm and dedication. Their interaction with the faculty was smooth and intense. The result is the current Report, which contains many interesting and original ideas and recommendations.

The development of AI/ML and the establishment of a permanent settlement on the Moon are two key features of the coming decade. This Report may be a significant reference for future work on them.

Enjoy reading!
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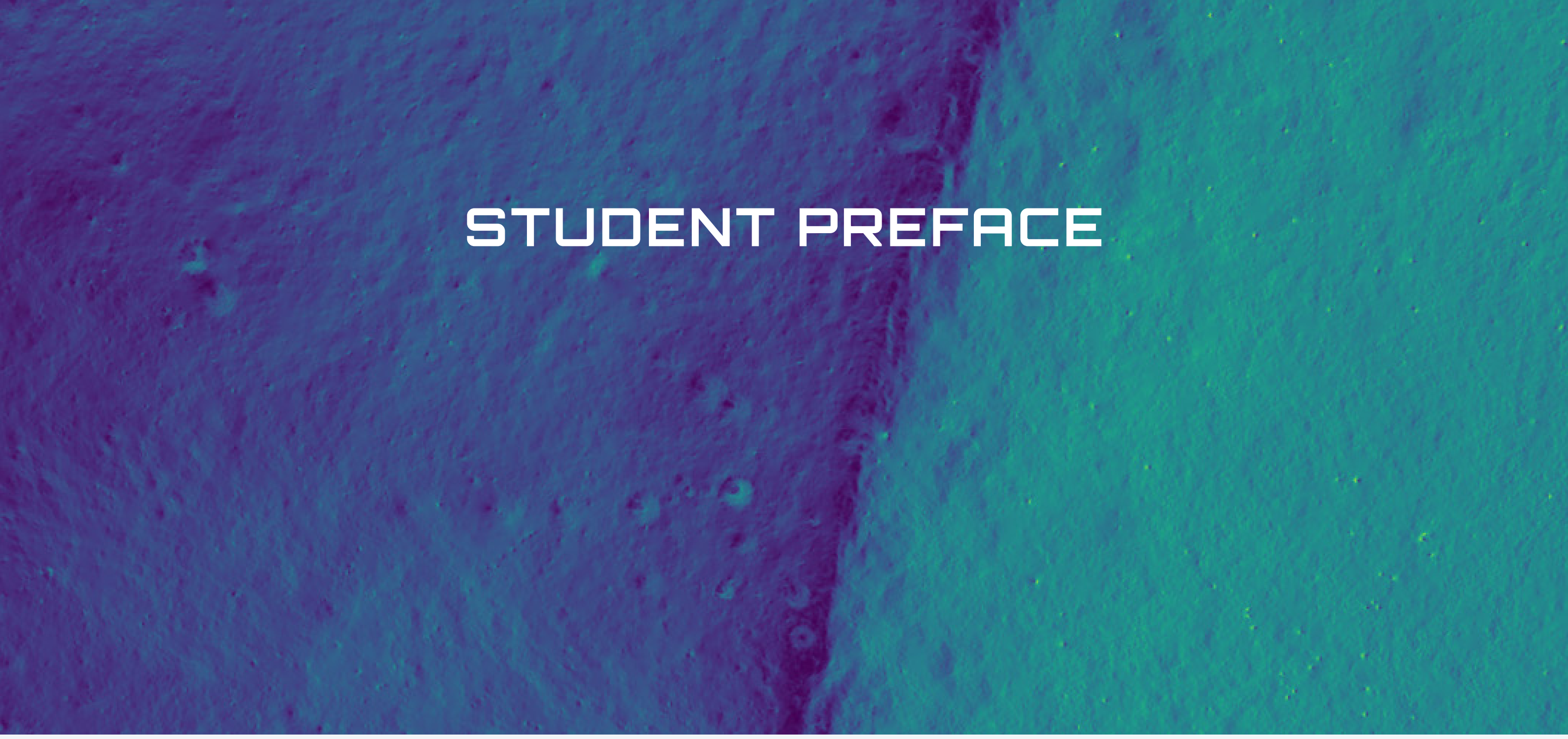

When Gene Cernan left the last footprint on the surface of the Moon in 1972 on Apollo 17, the return of humanity was an unknown. Now, fifty years later, the new space race has brought with it a reinvigorated global space sector and the opportunity to walk once more upon the lunar surface.

The first lunar outpost will be a defining moment in the history of humanity. The technological, ethical, legal, scientific, and human challenges this task poses will test the capabilities and perseverance of what must be a global effort. The success of this challenge will have been decades in the making, paving the path for innovation and advancement further out in the solar system. The risks and dangers of the space environment are conquerable by the determination, innovation, and ambition of those striving to further the reaches of humanity.

This project sought to help conquer those challenges not only by exploring foundational contributions that artificial intelligence and machine learning can make to humanity's first lunar outpost, but by strengthening the knowledge, skills, and enterprising spirit of the cohort that worked on it as well.

The beginning of the 2022 Southern Hemisphere Space Studies Program (SHSSP22) saw 34 participants gather the best of their own determination, innovation and ambition in preparation for what would be a truly transformational five weeks. While learning about the challenges and triumphs of space exploration, participants were also on their own personal journeys of leadership, teamwork and reflection. The program, created by the International Space University (ISU) and the University of South Australia (UniSA), brought together experts from around the world who shared their inspiring space journeys and enlightened us as to the state of space across the globe.

Throughout the team project, focus was given to the values of the ISU, ensuring an international, intercultural, and interdisciplinary approach. In addition to these, the cohort added our own three values of inclusion, inspiration, and imagination. We journeyed together, balancing leadership and followership, and celebrated the perspectives brought by each other's life experiences and careers.

The SHSSP22 cohort is incredibly grateful for the generous support and guidance provided throughout the program. We would like to acknowledge and thank all of the program staff and volunteers, guest lecturers, keynote speakers, academics, and IT support. A special thank you to our team project chair, Dr. François Spiero, and our team project associate chairs, Prof. Rodrigo Ventura and Dr. Jacques Arnould, for their advice and support over the course of this project. Their thoughtful advice and words of encouragement were guiding lights over this journey. It was an honor to have had the opportunity to work alongside them.

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ACRONYMS

AI	Artificial intelligence
AIaaS	Artificial-Intelligence-as-a-service
API	Application programing interface
CIMON	Crew Interactive Mobile companioN
COPUOS	Committee on the Peaceful Uses of Outer Space
DEM	Digital evaluation model
ESA	European Space Agency
GCR	Galactic cosmic radiation
GGE LAWS	Group of Government Experts on Lethal Autonomous Weapon Systems
ISRU	In-situ resource utilization
ISS	International Space Station
JAXA	Japanese Aerospace Exploration Agency
JPL	Jet Propulsion Laboratory
LOI	Lunar orbit insertion
LOLA	Lunar Orbiter Laser Altimeter
LRO	Lunar Reconnaissance Orbiter
ML	Machine learning
NASA	National Aeronautics and Space Administration
OST	Outer Space Treaty
PSR	Permanently shaded region
SELENE	SELonological and ENgineering Explorer
SEP	Solar energetic particle
SPE	Solar particle event
THEMIS-ARTEMIS	NASA Heliophysics satellite constellation
UN	United Nations
UNESCO	United Nations Educational, Scientific, and Cultural Organization
USA	United States of America
USD	United States Dollar
VIPER	Volatiles Investigating Polar Exploration Rover

1 INTRODUCTION

Fifty years after the last human exploration of the lunar surface, humanity is once again preparing to set foot on the Moon. Advances in technology, particularly in artificial intelligence (AI) and machine learning (ML), mean new tools and capabilities can be brought to bear on the challenge of lunar exploration and settlement. The Southern Hemisphere Space Studies Program 2022 cohort seeks to contribute to the global discussion about how these capabilities can be best employed in the context of a future lunar outpost. This report is the culmination of an intensive, interdisciplinary research project on the following theme:

> ***"Enabling humanity's exploration of space through an interdisciplinary approach to using artificial intelligence and machine learning for the optimization of a sustainable lunar outpost."***

1.1 PURPOSE

AI and ML are powerful tools that have the potential to contribute to space mission planning. A future lunar outpost will be a complex, costly, and dangerous undertaking, and effective mission planning will be critical to its success and longevity. This planning must encompass a wide range of specifications, including the location of the lunar base, the safety and wellbeing of its inhabitants, and the commercial and scientific activities the outpost will enable. The establishment of a long-term human settlement on the Moon will also have significant ethical, legal, geopolitical, and cultural implications. This report aims to demonstrate how AI and ML can be harnessed to optimize specifications for a sustainable lunar outpost and highlight the legal, cultural and ethical implications of doing so.

1.2 APPROACH

AI and ML were considered from the perspectives of seven space-related disciplines: space applications; engineering; management and business; human performance; science; humanities; and policy, ethics and law. A wide-ranging literature review identified nine key specifications across five of these disciplines (applications, engineering, management and business, human performance, and science) with strong potential to benefit from the application of AI and ML. Of these, five specifications were linked by the common criterion of optimizing the location of a lunar outpost. These specifications were analyzed in greater depth and used to develop a proposed AI and ML tool. One specification was then selected for prototyping to demonstrate the value of the proposed AI and ML system.

Chapter 2 provides an interdisciplinary discussion of the requirements of a lunar outpost and identifies the five specifications for optimization with AI and ML tools. Chapter 3 identifies knowledge gaps related to the down-selected specifications and suggests future lunar missions needed to close these gaps. Chapter 4 provides an in-depth discussion of the functional requirements relevant to the five specifications and provides the results of a prototype demonstration. Chapter 5 discusses the policy, ethical, legal, and cultural considerations of the AI and ML system proposed in Chapter 4, as well as potential future applications for this system. Chapter 6 provides a roadmap and visualization of the steps required to employ the proposed AI and ML system to optimize a lunar outpost location.

1.3 DEFINITIONS

1.3.1 Artificial Intelligence

Artificial intelligence is described as intelligence demonstrated by machines rather than by natural occurrence which mimics the human mind's problem-solving and decision-making capabilities (McCarthy, 2004). AI is a broad category, encompassing a range of technologies including natural language processing, computer vision, machine learning, and robotics.

1.3.2 Machine Learning

Machine learning methods are computational methods that use information about past system behavior to improve the current system's performance (Mohri, M. 2018). ML involves designing learning and prediction algorithms, and data-driven techniques that combine ideas from probability and statistics with computer science and data science (Mohri, M. 2018). The performance of learning algorithms, and overall ML systems, is dependent on the quality of the data with which the system is trained.

1.3.3 Lunar Outpost

The lunar outpost envisioned in this report would be the first long-term human settlement on the Moon. Commercial entities would contribute to the development and operation of the outpost. The lunar environment will provide resources for sustaining aspects of the lunar outpost, and as technology develops the outpost would evolve towards self-sufficiency. The inhabitants would live on the Moon for long periods with a quality of life far superior to that of past expeditions to the lunar surface. Although the outpost design is beyond the scope of this study, the report assumes an outpost that provides everything required for humans not just to live, but to thrive, on the Moon for years.

2 BACKGROUND

This chapter discusses the potential for AI and ML to optimize specifications and characteristics of a lunar outpost from a multidisciplinary approach, including space applications; engineering; management and business; human performance; science; humanities; and policy, ethics, and law disciplinary perspectives.

2.1 SPACE APPLICATIONS

AI and ML are powerful tools already applied across various systems, with several opportunities for application in lunar missions. One key application is intelligent sensing (AI applied to remote sensing), which offers a solution to challenges in lunar prospecting, surveying (Jawin, et al., 2018), and exposing surface changes (Jonsson, et al., 2007). Building on past remote sensing techniques such as photogeology and reflectance spectroscopy (Dunkin and Heather, 2000), intelligent sensing can apply high-resolution anomaly detection and data fusion processes to compare large amounts of data and provide a comprehensive understanding of the lunar surface (Jung, et al., 2021; Varatharajan, et al., 2021). Intelligent sensing will be crucial for handling navigation, data analysis, and decision making without assistance from mission control (Oche, Ata and Ibekwe, 2020). For the purposes of a lunar outpost, intelligent sensing techniques can optimize the location for both solar exposure and terrain access.

2.1.1 Specification 1: Optimizing a lunar outpost location for solar exposure

AI and ML have applications in laser altimeter-derived topography to learn solar exposure conditions. The construction and tracking of an average solar exposure map are tasks that intelligent sensing can perform, along with the tracking of eclipse periods and the determination of regions with maximum solar exposure. This can contribute to outpost location optimization, as solar exposure is critical for aspects such as power generation (Bussey, et al., 2010) and thermal control systems (Fraser, 2012). An AI acting on dedicated digital twin models of temperature-sensitive equipment could govern active thermal control systems, ensuring that temperature requirements are constantly satisfied (Dunbar, 2021). Meanwhile, the plan for developing nuclear reactor power systems initiated by NASA is a promising alternative solution for human settlements on the Moon and Mars (Soderman, 2009).

2.1.2 Specification 2: Optimizing lunar outpost location for terrain access

AI and ML can determine an optimal safe landing zone factoring in terrain navigation, to avoid terrain hazards for the lander and rover and minimize risk. Computer vision methods and optical sensors could identify obstacles such as craters and boulders. The implementation of combinatorial optimization algorithms can select the optimum path across the surface for the mission plan (Lavin, 2015). The incorporation of AI into guidance and navigation, particularly for autonomous or automated systems, would improve risk mitigation (Jonsson, et al., 2007).

2.2 SPACE ENGINEERING

AI and ML can optimize multiple engineering aspects of a lunar outpost mission, including astrodynamics and mission analysis, space systems engineering, propulsion, attitude dynamics and control, communications, and robotics. Two aspects identified as particularly benefiting from the incorporation of AI and ML include the fuel mass budget for orbital transfers and identifying a suitable outpost location for access to resources.

2.2.1 Specification 3: Optimizing orbital transfers for fuel mass budget

Optimizing the trajectory and orbit of launch vehicles will be crucial to the success of a lunar outpost mission. Loitering in low lunar orbit as a means of reducing the insertion delta-v, and hence minimizing the fuel needed to take the spacecraft into the preliminary orbit, can optimize the overall lift-off mass of the mission (Garn, et al., 2008). This permits the transport of larger payloads to the lunar surface, therefore supporting the establishment and operation of a lunar outpost.

2.2.2 Specification 4: Optimizing lunar outpost location for resource access

Access to resources will be critical for the sustainable development of a lunar outpost, including oxygen and water for human needs, regolith and rock for construction, and metals for manufacturing. Recent research includes pyrolysis, electrolysis, and sulfuric acid treatment as options for extracting oxygen (Schwandt, et al., 2012). Lunar surface volatile identification via radar sensing is possible, however the sensitivity of radar backscatter with surface parameters is highly nonlinear and empirical methods yield unreliable results. ML has provided robust methodologies and automatic techniques in radar science because of its capability to handle multivariate, highly complex data that is nonlinear.

AI-based approaches for evaluating radar responses relevant to surface and sub-surface volatile sensing can play an important role in prospecting target regions for in-situ resource utilization

(ISRU) (Varatharajan, et al., 2021). Because it is an essential element for sustaining life, optimizing a location for access to water ice is an essential component of resource access and, since its discovery on the Moon, has become a key focus for future lunar missions.

2.3 SPACE MANAGEMENT AND BUSINESS

The development of a lunar outpost requires a comprehensive and well-developed business strategy to ensure feasibility, sustainability, and profitability through the commercialization of innovative ideas. Due to innate cognitive biases, human decision-making is inherently flawed and can lead to suboptimal business decisions (Kramer, 2016; Allen, Lyons and Tavares, 2017); which could be a prohibitively costly flaw when applied to the establishment of a lunar outpost.

The use of carefully curated AI and ML tools can optimize business decision-making for a lunar outpost, drawing on existing practices that optimize financial decisions and improve both predictability and performance (OECD, 2021). The increased deployment of AI in a business context is expected to drive competitive advantages through optimized efficiencies, productivity enhancement, and personalized product and service offerings (Golic, 2019). Leveraging terrestrial applications of AI, ML and Big Data will be crucial to enhancing lunar base economic sustainability.

AI and ML have limitations, however, due to the dynamic and changing nature of financial systems and business models (Gulati, Bacharach and Bamberger, 2007) and non-standardized and incomplete datasets, which also may come with bias (Allen, Lyons and Tavares, 2017). Daníelsson, et al., (2021) analyzed the role of AI in financial systems, noting that AI and ML tools function best when given immutable rules with predetermined bounded actions, and concise objectives.

Two specifications have been identified that would support the establishment of a successful and sustainable lunar outpost and have strong potential for optimization using AI and ML. These were selected based on the large existing datasets from Earth-based commercial applications of AI and ML that could be applied to the lunar context.

2.3.1 Specification 5: Optimizing profitability and cost efficiency in manufacturing across the lunar outpost development

AI and ML has applications in the cost-benefit analysis of manufacturing on the Moon versus transporting supplies and materials from Earth. Transportation is expensive, averaging $42,400 USD per kilogram to the surface of the Moon (Isakowitz, Hopkins and Hopkins Jr, 2004). The ISU 2006 Master’s Program final report, Fertile Moon (Belachgar, et al., 2006) presents a parameter analysis of ISRU water production compared to launching hydrogen and oxygen from Earth. Business decisions were dependent on mission time, machine performance, and Moon-based trading options. AI is well suited to incorporating these supply parameters into payload planning to support manufacturing. Chien, et al. (1999) have shown early examples of automated planning and scheduling of shuttle payload operations. Training ML to plan lunar activities using asset availability and payload logistics parameters can optimize operations and maximize business outcomes.

2.3.2 Specification 6: Optimizing global customer engagement and awareness of the lunar outpost

The high cost and complexity of establishing a lunar outpost will likely require international collaboration and burden sharing between the public and private sectors. Strategic engagement with the public will be critical to maintaining the outpost’s social license to operate. The importance of public support cannot be overstated when considering the ongoing sustainability of space exploration; after the Apollo program of the 1960s, the decrease in public engagement and loss of political support led to a significant reduction in NASA's annual operating budget (The Planetary Society, 2022). Negative public opinion towards space activities has the potential to create significant capital losses (Van Til, 2013). This can be counteracted by applying AI and ML tools to marketing, consumer research, public engagement, and psychology (Mariani, Perez-Vega and Wirtz, 2021).

Public and private organizations are increasingly using AI and ML to provide improved customer experiences, personalization, and individualized product value propositions (Rai, et al., 2021). Decision-makers can use AI and ML to enhance their understanding of the outpost's global audience to target engagement efforts effectively, and in a culturally appropriate manner.

2.4 HUMAN PERFORMANCE IN SPACE

There are five principal hazards that will affect humans during long-term space flight: radiation; reduced gravity; hostile environments; isolation; and the distance from Earth (Human Research Roadmap, 2019). These hazards will directly affect mission success if not mitigated appropriately. NASA has identified a multi-disciplinary approach as the best way forward, considering biological, psychological, social, and environmental factors (Schorn and Roma, 2020).

AI and ML can help to address the challenges of isolation and confinement on the lunar surface. Advances in monitoring technology are enabling devices to detect, evaluate, and respond to emotional and physical states (Luxton, et al., 2016). These can be used as wearable devices, assistant robots, or embedded within an environment.

CIMON (Crew Interactive Mobile companioN), a free-floating AI robot developed by IBM for use on the International Space Station, was developed with the intention of providing companionship to humans. CIMON uses AI and ML together with facial-recognition software to recognize who is talking and interacts by showing basic facial expressions. CIMON aims to increase efficiency, psychologically support astronauts, and make the astronauts' workflow more fluid by providing an objective point of view, finding information faster, and documenting experiments. (IBM, 2020).

Australian companies A.KIN and Fortifyedge are working with NASA to develop AI systems to support astronauts in space. A.KIN is developing AI avatars and robots to support the crew intellectually and physically, look for changes in environment, and operate as an overarching "brain" to understand the habitat as a whole (a.kin, 2021). Fortifyedge is developing wearable devices using advanced behavioral biometrics to determine user health, safety status, and system security (Fortifyedge, 2021).

Considering human requirements and current AI and ML capabilities, two specifications have been identified that can be optimized for human performance: minimizing environment impacts and personalized monitoring and assessment of the crew's condition.

2.4.1 Specification 7: Optimizing lunar outpost location to minimize the environmental impacts on crew health

Locating the base on a site that will minimize the environmental risks to its crew is of the utmost importance. This includes finding a location with minimal temperature variations; factoring in sun position to accommodate diurnal cycle (Advancing Earth and Space Science, 2020); and limiting the amount of hazardous lunar dust that may endanger crew (James and Kahn-Mayberry, 2009). AI and ML can be used to analyze locations for these risks, for example minimizing radiation exposure by assessing local lunar magnetic fields (Korte, 2020), and topographical effects on solar exposure.

2.4.2 Specification 8: Optimizing the monitoring and personalized assessment of the physical and psychological condition of the crew

AI and ML can enable less Earth-dependent health system assessment by using physiological and behavioral data collected by wearable sensors. For example, NASA's LifeGuard system monitors astronauts' physiological responses to a changing environment via multi-signal monitoring equipment (Glaros and Fotiadis, 2005). AI can analyze and distribute biological information to the astronaut and medical team to guide and recommend actions to maintain health and wellbeing, including:

- tracking hydration requirements and heart rate reduction (Pierce, 2021);
- monitoring stress and fatigue through acoustic analysis (Scalon, 1998); and
- diagnosing mental health disorders (Frankel, 2016).

2.5 SPACE SCIENCE

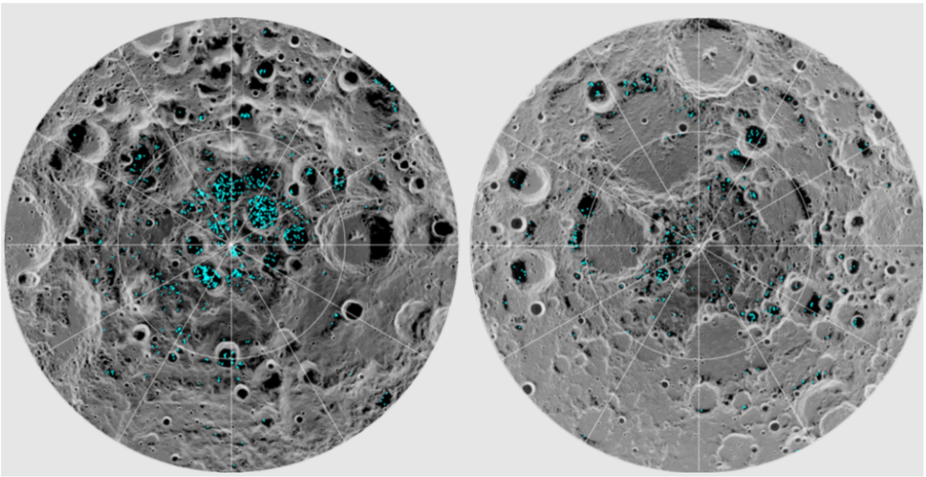

Figure 1: Lunar poles heat intensity map (lighter regions are warmer), with ice overlay (blue) (NASA, 2018)

The scientific community already produces a range of data products that are good candidates for AI and ML analysis, such as Figure 1, which shows imagery of ice on the lunar pole detected by NASA's Moon Mineralogy Mapper instrument (Tavares, 2018). Software such as NASA ISIS3 has been used to analyze lunar data to determine suitable lunar outpost locations (Detsis, et al., 2013). As the planetary sciences community continues to gather large volumes of scientific data at a rate exceeding what can be processed by people and software packages alone, AI and ML will be critical to creating meaningful insights and new discoveries in space exploration (Azari, et al., 2020).

AI and ML applications in the geosciences field such as pattern detection, event characterization, and classification can be applied to space sciences to further benefit the understanding and exploration of the lunar environment (Karpatne, 2019). Possible space science applications include resource mapping, surface exploration and lunar soil classification (Kodikara and

McHenry, 2020; Varatharajan, et al., 2021). Wenxiang, et al.,(2019) have already used neural networking algorithms to generate maps of lunar surface composition such as the major oxide distributions, which is critical surface geological information for understanding the petrological characteristics of the lunar environment. This suggests AI and ML tools are well suited to optimizing both the location of potential research sites on the lunar surface and the location of the outpost relative to sites of scientific interest.

2.5.1 Specification 9: optimizing lunar outpost location for access to diverse scientific sites of interest

The lunar environment offers a range of opportunities for exploration, improving technology readiness level of future missions, and scientific study. The lunar permanently shaded regions (PSRs) function as cold traps due to the lack of solar radiation, thus enabling access to preserved materials brought to the Moon through meteorite impacts such as meteoric iron, carbon compounds, and water (Moye and Lee, 2020). According to Meyer (2003), the breccia that form after a meteorite impact are often high in aluminum oxide, which is an important compound for protecting against radiation as well as oxygen and water production, thereby placing breccia as an important area of scientific study. An investigation of elemental abundances on the Moon and crustal thickness may reveal insights on the elemental distribution across the solar system and past heating processes of the Moon, particularly investigations of the deep basins and large impact sites (Sohl and Schubert, 2015; Wieczorek, 2007; Taylor, 2007).

AI and ML can optimize planning expeditions for scientific purposes, identifying sites that maximize scientific value and minimize risk to scientists such as those from radiation, regolith, extreme temperatures, and surface impacts (Benaroya, Bernold and Chua, 2018; Grün, Horanyi and Sternovsky, 2011; Wilhelm and Curbach, 2014). Using existing lunar data, AI and ML can optimize locations for conducting lunar experiments in seismology, geology, astronomy, and other fields. Siting a lunar outpost in proximity to multiple sites of scientific interest would reduce both the cost and risk associated with conducting scientific research on the Moon. By examining lunar topological and geological data, AI and ML can optimize the lunar output location to maximize returns from surface studies. This may also include consideration of the site topology and the compatibility for establishing infrastructure such as additional habitats to house and facilitate space science studies.

2.6 ETHICAL, CULTURAL AND REGULATORY CONSIDERATIONS

Using AI and ML to optimize the establishment of a lunar outpost poses not just technical challenges, but also ethical, cultural and regulatory challenges. There is first the fundamental question of how to responsibly and legally establish a settlement on the Moon, which encompasses issues relating to the Moon's lack of sovereignty (Art II, OST); Moon heritage (Lixinski, 2022); and environmental concerns (Cain, 2008).

Using AI and ML to help establish a lunar outpost adds another layer for regulatory and ethical consideration: how can the use of AI and ML in space be effectively regulated, and can AI and ML be used to optimize the cultural, legal and ethical aspects of a lunar outpost.

The current normative framework (which is silent on AI and ML capabilities) would enable AI and ML use on the Moon, in the same way other tools can be used to implement human decision-making. Unlike other tools, however, AI and ML can recommend, or even decide upon, certain actions being taken. The significance of this, and the risks associated with space settlement, means that the framework (comprised of legal, policy and ethical factors) can no longer remain silent on the issue.

2.6.1 Humanities

Given the vast social and cultural impacts of space and lunar exploration (Fellow, 2011; Smith, 2009), it is reasonable to assume that the establishment of humanity's first lunar outpost will also have significant social and cultural dimensions. The contribution of research underpinned by humanities methodologies and techniques (Lukaszczyk and Peter, 2009) complements the well-established technical, scientific, national security, legal, and economic perspectives on lunar exploration. Key considerations for a lunar outpost from a humanities perspective include the cultural significance of the future lunar outpost and the impact of the outpost on the natural heritage of the lunar environment (O'Leary, 2009, pp:757-780; Australian Earth Laws Alliance, 2022).

Like the Apollo 11 artifacts in the Tranquility Base site (Gorman, 2005), a future lunar outpost would have national and global cultural significance because of its connection to humanity's first off-Earth settlement, and the physical and digital artifacts associated with the establishment of the outpost would likely be imbued with deep cultural value. This would extend to AI or ML systems employed to optimize aspects of the outpost, integrating these systems into an interplanetary cultural landscape (Gorman, 2005).

The Moon has significance to cultural practices and belief systems around the world, such as celebrations of lunar new year in several East Asian cultures and mythologies in First Nations communities in Australia, the United States and Canada (Brunner, 2010). The impact of the creation of a lunar outpost on the natural and cultural heritage value of the lunar environment is still unknown, but analogs like the impact of light pollution from space systems on Indigenous astronomy practices demonstrate the potential for tension between space exploration and cultural practices and beliefs (Harris, 2009; Sokol, 2021).

Planning the first human lunar outpost will require an understanding of the impact of lunar settlement on all cultures, not just those with access to space. The limitations of AI and ML, mainly related to the inherent algorithmic biases and the handling of sensitive data (Brubaker, 2018; Fast and Horvitz, 2017), suggest that significant caution must be taken to ensure that algorithms used for determining specifications of the lunar base reflect the values of all cultures, spacefaring or not.

The natural heritage of the Moon is not yet recognized in a legal framework, aside from general notions of non-appropriation, but there is a nascent movement to recognize the Moon as a 'sovereign natural entity in its own right' (Australian Earth Laws Alliance, 2022).

Although culture and heritage are important specifications when establishing a lunar outpost, they are poor candidates for optimization using AI and ML tools. Cultural and natural heritage value is difficult to quantify, and measures of cultural value, such as those found in the United Nations Educational, Scientific, and Cultural Organization (UNESCO) World Heritage Criteria (UNESCO 2013, p.36), rely primarily on qualitative assessments of such value. Heritage evaluation consists of assessments of "symbolic meaning(s) that relate to societal structures, human relationships, language, myth or behaviors" (Walsh, 2011, p. 237) that are not easily normalized or counted.

As the ability to create consistent and reliable training data does not yet exist (Stewart, 2019), social and cultural dimensions of a lunar outpost will be difficult to optimize with AI and ML. Human intervention is necessary to build meaningful insights based on what is necessarily qualitative, contextual and subjective analysis. (Mahto, et al., 2020).

2.6.2 Space policy, ethics and law

At the heart of space regulation are five space treaties:

- *Treaty on Principles Governing the Activities of States in the Exploration and Use of Outer Space, Including the Moon and Other Celestial Bodies*, also known as the Outer Space Treaty (OST)
- *Agreement on the Rescue of Astronauts and the Return of Astronauts and the Return of Objects Launched into Outer Space* (Rescue Agreement)
- *Convention on International Liability for Damage Caused by Space Objects* (Liability Convention)
- *Convention on Registration of Objects Launched into Outer Space* (Registration Convention); and,
- *Agreement Governing the Activities of States on the Moon and Other Celestial Bodies* (Moon Agreement).

These treaties were created when space was still largely inaccessible (de Zwart, 2021. p.66). The authors did not envision the rapid advancements in technology that have occurred since that time (Freeland, 2017), nor did they contemplate non-State entities conducting commercial space activities (Davis and Lee, 1999).

A new normative framework is needed to ensure space law and regulations is fit for purpose for lunar missions. There is currently no international law that governs AI and ML (Burri, 2017). Additional complexity is created by 95% of technological advancements being considered dual use (can be used for civilian and military objectives) (Johnson-Freese, 2007, p.30). Given the intention of the OST to maintain space use solely for 'peaceful purposes', and the fact that dual-use technologies can be used for peaceful and non-peaceful purposes, stronger regulation, driven by the United Nations (UN) Committee on the Peaceful Uses of Outer Space (COPUOS), is needed to ensure legal compliance.

International entities have been established to discuss the normative framework for AI and ML, most notably the UN Group of Government Experts on Lethal Autonomous Weapon Systems (GGE LAWS) (UN, 2019). Although the GGE LAWS focuses on international humanitarian law, many of the legal and ethical issues raised are transferrable to AI and ML use in the space domain. These include: the 11 guiding principles agreed by the GGE (UN, 2019. Annex IV); the need to deploy AI and ML capabilities within a responsible chain of control (Ulgen, 2018); the requirement for human responsibility throughout the lifecycle of the AI and ML capability (UN, 2019, Annex IV); the debate surrounding human-machine interaction and the level of human involvement required for international law compliance (Digwatch, 2021); the ethical and moral concerns surrounding the risks posed by these technologies, and in particular data bias (UN, 2017) and security concerns (Reznik, 2022); the need for risk mitigation (Geiss, 2016); and what restrictions should apply to AI and ML as a matter of law or policy (if any).

AI and ML can assist in establishing a lunar outpost, however regulatory reform will be required to fully support such a mission. This will not be easy given the OST requirement for international consensus. The current geopolitical climate - and the need to reflect global community values, not just those of the capable few (Krichevsky and Bagrov, 2019) - suggests unanimous change is unlikely. This will leave policies, such as the Resolution on Responsible Behaviors in Space (Office for Disarmament Affairs, 2021), to fill the regulatory void moving forward.

2.7 DOWN-SELECTION OF SPECIFICATIONS

This chapter has identified nine specifications of a future lunar outpost that can be optimized using AI and ML tools. Five of these specifications relate to the identification of a suitable outpost location:

- Optimizing lunar outpost location for solar exposure
- Optimizing lunar outpost location for terrain access
- Optimizing lunar outpost location for access to diverse sites of scientific interest
- Optimizing lunar outpost location to minimize environmental impacts on crew health
- Optimizing lunar outpost location for resource access

Focusing on these five specifications, the following two chapters will explore a multi-disciplinary approach to how AI and ML can be used to optimize identification of a lunar outpost location.

3 KNOWLEDGE GAPS

Table 1 identifies key knowledge gaps relating to the proposed specifications for a lunar outpost and describes the types of lunar missions needed to gather additional information for analysis. Further discussion of the identified knowledge gaps is provided at Appendix A.

Table 1: identified key knowledge gaps relating to proposed specifications

Specification	Key knowledge gaps	Types of missions recommended to address gaps
Solar Exposure	Insufficient resolution in available illumination, slope, and roughness data derived from current remote sensing products	Remote sensing mission to provide higher resolution data and identify peaks on the lunar surface
Terrain Access	Training data for terrain traversal prediction	Surface missions for collection of surface density data Core sampling missions on surface hardness and layering
Diverse Scientific Sites	Quality of available remote sensing products Characteristics of lunar lava tubes	Remote sensing mission to improve available data quality Rover mission to explore lava tubes
Environmental Health Impact	Active radiation dose measurements on the lunar surface	Rover mission to measure radiation levels and collect surface samples Fusion of rover mission data with remote sensing data
Access to resources	Processes for utilizing Lunar regolith rather than simulant Extraction of water and oxygen in-situ	Rover missions to assess water and oxygen extraction feasibility Large scale sample collection and in-situ processing tests

4 DESIGN METHODOLOGY

This chapter discusses the design methodology and functional requirements for a system intended to optimize the selection of a lunar outpost location based on the selected five specifications. The functional requirements provide the system with site preferences and quantitative parameters. They ensure the five selected specifications are developed into measurable inputs for the system.

4.1 FUNCTIONAL REQUIREMENTS

The six identified functional requirements are:

- The system shall produce coordinates where all-source radiation is less than 500 mSv/yr
- The system shall produce coordinates where there is an accessible and viable solar power site
- The system shall prefer sites that are shielded from solar wind events
- The system shall produce coordinates for flat regions and terrain accessibility
- The system shall prefer sites with access to resources for both vehicles and astronauts
- The system shall produce coordinates that provide access to diverse chemical and geological features

Each functional requirement is discussed in more detail below.

4.1.1 The system shall produce coordinates where all-source radiation is less than 500 mSv/yr

It is essential to limit radiation exposure for inhabitants of a lunar outpost to minimize the numerous associated chronic health effects (Zhang, et al., 2020). Consensus limits for astronauts aboard the International Space Station (ISS) permit an annual exposure of 500 mSv and a career limit of 1,000 mSv (Cucinotta, 2010), which can be used as an appropriate model for the lunar outpost. Considering factors such as localized magnetic fields (Blewett, et al., 2020), latitude, and the shadowing effect of the nearby elevated terrain (Cooper, 2016), it is possible to identify suitable locations. One such location was identified by the Lunar Lander Neutrons and Dosimetry experiment aboard China's Chang'E 4 lander (Zhang, et al., 2020).

4.1.2 The system shall produce coordinates where there is an accessible and viable solar power site

An understanding of solar exposure is critical for a successful mission to the Moon for energy generation (Speyerer and Robinson, 2013). Solar sites with sufficient exposure will ensure that energy generation meets the ongoing requirements of the outpost (Boro, 2020) before the commissioning of a nuclear reactor on-site, with sufficient batteries or an equivalent device for energy storage to supplement and support the primary power source. In addition, solar exposure data can inform modeling and design for thermal control systems, for application in lunar infrastructure such as electronics, habitats, and rovers (Fraser, 2012). The Lunar Reconnaissance Orbiter and other craft such as SELENE, Chandrayaan-1, and Clementine produce suitable data for this purpose (Speyerer and Robinson, 2013).

4.1.3 The system shall prefer sites that are shielded from solar wind events

For mission planning and analysis, an understanding of space weather events such as solar winds will be vital for the selection of a lunar outpost. The outpost will, at a minimum, contain sensitive communication and operation equipment similar to that of the Apollo missions (Dunbar, 2019), which will require protection from solar winds. Previous NASA missions, including the Advanced

Composition Explorer, and the Cluster and Wind missions (Arvidson, 2022), have studied lunar solar radiation patterns, as will the upcoming NASA Heliophysics constellation of satellites (THEMIS-ARTEMIS). This provides invaluable data on the solar-lunar relationship and how solar particle events affect the lunar surface (Folta, 2010).

4.1.4 The system shall produce coordinates for flat regions and terrain accessibility

Identifying areas of high accessibility minimizes the risk of entrapment events, a critical aspect for the success of robotic missions (Callas, 2015). The optimum location for a lunar outpost would be a sizable flat region to enable unimpeded expansion. For outpost placement, slopes below 10° are acceptable, given that 15° is hazardous for landing vehicles (De Rosa, et al., 2012). The Volatiles Investigating Polar Exploration Rover (VIPER) can traverse 15° slopes (and some higher inclinations in times of necessity) (Chen, 2020; Wetzel, 2021). With these considerations in mind, outpost location should consider accessibility for vehicles and astronauts. This accessibility ensures efficiency of transportation and efficient use of astronaut time on the surface, outside of the lunar outpost.

4.1.5 The system shall prefer sites with access to resources for both vehicles and astronauts

Humans living on a lunar outpost will require access to resources for long-term survival and it is not always feasible from a cost and logistics perspective to continuously bring resources from Earth. Access to lunar resources for both vehicles and astronauts will be crucial for a sustainable and efficient lunar outpost. The background information for specification 4 in Chapter 2 outlines the resources available on the Moon and how they may benefit human exploration on the lunar surface. The location of these resources must be factored into the selection of a lunar outpost location to ensure its inhabitants have access.

Locating an outpost near particular resources, such as minerals or water ice, will allow the outpost to function sustainably and simplify long-term planning of outpost resource management. Preferencing locations near significant water resources will be critical to establishing a sustainable long-term outpost. The ability to use resources from the Moon provides both engineering and sustainability benefits, for astronauts to not just survive, but thrive on the Moon, and for engineering advancements.

4.1.6 The system shall produce coordinates that provide access to diverse chemical and geological features

As mentioned in Chapter 2, there are many factors that are crucial to scientific objectives on the lunar surface such as PSRs, breccia and a diverse range of elements. Studying the deposits left by meteorites may also aid in the understanding of conditions in early nebula and early planets (Norman, M 2004). By preferencing these sites when determining a lunar outpost location, it ensures that scientifically diverse areas are more accessible to astronauts on the outpost. Significant scientific learnings will be made increasingly possible by direct access to the lunar surface. In-situ experiments and resulting data will reduce delays and increase data quality. The potential ongoing benefit from those learnings mean that preferencing a lunar outpost location for scientific diversity may support many future missions, both lunar and on other planetary bodies.

4.2 PROPOSED FRAMEWORK

Figure 2.

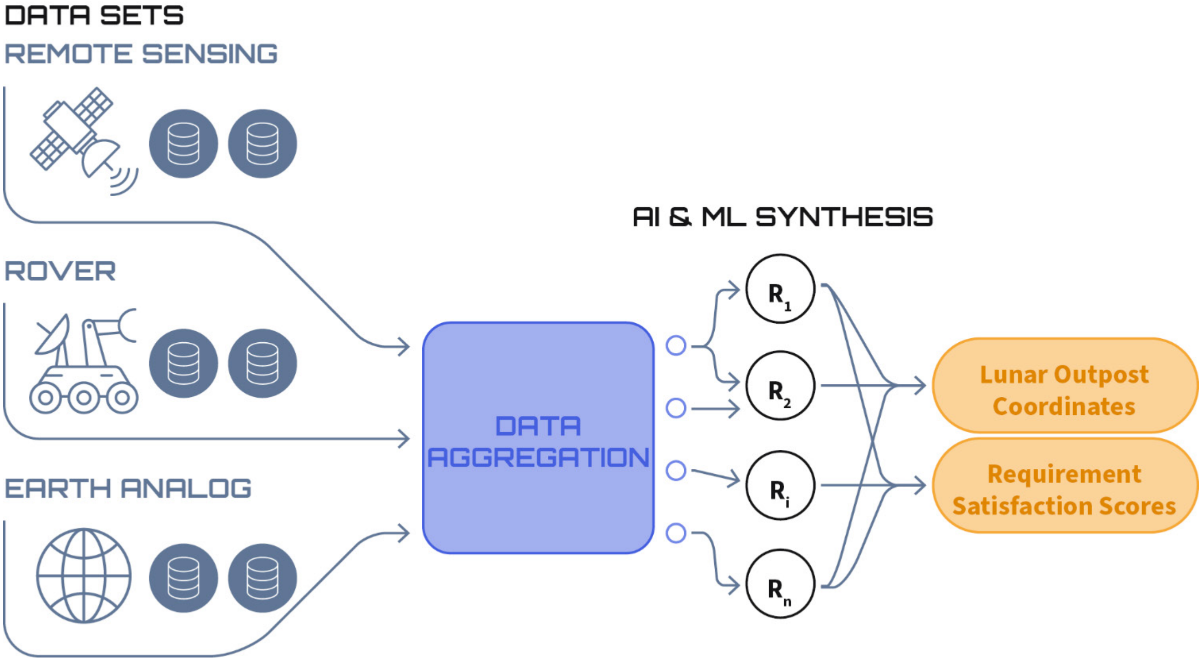

Figure 2: Proposed System Data Flow and Analysis

It is envisioned that the data aggregation module will be stored on a server that will gather and route all data collected from the real-time rovers, remote sensing, and earth analogue datasets. An application programming interface (API) will be vital to ensuring smooth communications between these datasets and the data aggregation server. This is designed to be a representational state transfer API (a web platform for the clients and servers to communicate using the hypertext transfer protocol). The data aggregation module can then send the aggregated data to a purpose-built AI server that receives the training data and carries out the necessary data cleaning and learning.

A range of hardware, from dedicated server banks through to a graphical processing unit network, will be required to train and develop the AI and ML algorithms on the AI and ML server. The following section demonstrates the feature extraction and basic AI implementation, as this is where most of the work for the system lies.

4.3 PROTOTYPE MODEL

This section outlines a prototype demonstration optimizing a lunar outpost location for terrain accessibility. This demonstration shows how the system can use existing data to suggest a location for a future outpost. This proposed prototype solution directly addresses two of the functional requirements identified in this chapter, including:

- The system shall produce coordinates where there is an accessible and viable solar power site
- The system shall produce coordinates for flat regions and terrain accessibility

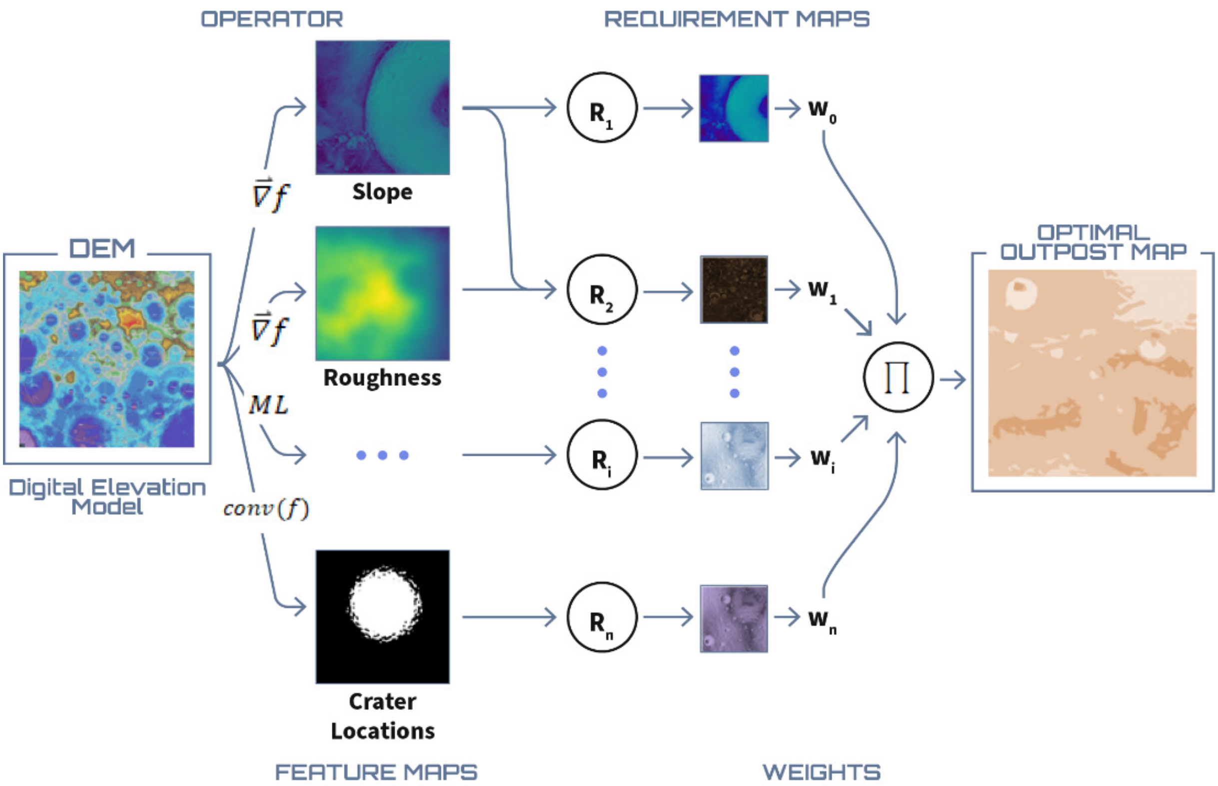

Figure 3: Flow chart demonstrating the key operators, feature maps, requirement maps, and weights for the prototype system, along with the optimal outpost map that is generated

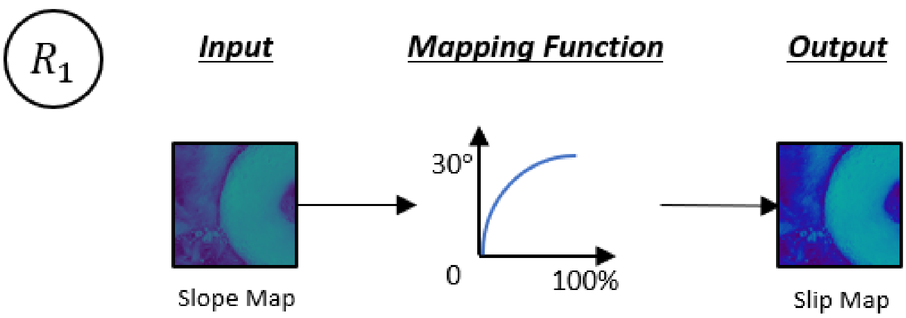

Figure 4: Example Requirement mapping function

High resolution DEMs are available for the lunar region from the Lunar Orbiter Laser Altimeter (LOLA). These models also contain information about the slope and roughness of the terrain. A recent study (Barker, 2021) has produced DEMs of 26 high-priority landing sites in the lunar south pole. These DEMs have a resolution of 5 meters per pixel and cover approximately 20 km squared. The resource also publishes slope maps for the same areas reducing the need to compute them manually. Although these DEMs are currently the highest resolution available, they do not have sufficiently high resolution to identify features less than five meters in diameter, which limits their effectiveness for the simulation of locomotion behavior. Fusing of higher resolution visual maps allows for smaller features such as boulders or craters to be included, but this is out of the scope of this prototype.

From the dataset used, Site01 was selected as the DEM for the development of this prototype as it has the highest average illumination and has complex topology. The prototype model uses available data from the VIPER rover's slope testing to provide constraints on the rovers' slip behavior in regolith, so that any path line planned will prevent likely entrapment events. The model can use these parameters to classify the terrain slope in terms of the estimated slip the rover might encounter. The characteristics of robotic locomotion derived from the VIPER locomotion platform are representative of the current state of work in robotics. These parameters are modifiable to consider different locomotion systems, such as historical systems and emerging robotic technologies.

4.4 PROTOTYPE RESULTS EXEMPLAR

Figure 5 and Figure 6 illustrate that analysis of locomotion parameters reduces the search space for optimal outpost locations significantly, but it does not identify an outpost location in the DEM. Increasing the number of requirements provided to the system will greatly increase the optimization criteria and would allow the system to determine suitable outpost locations.

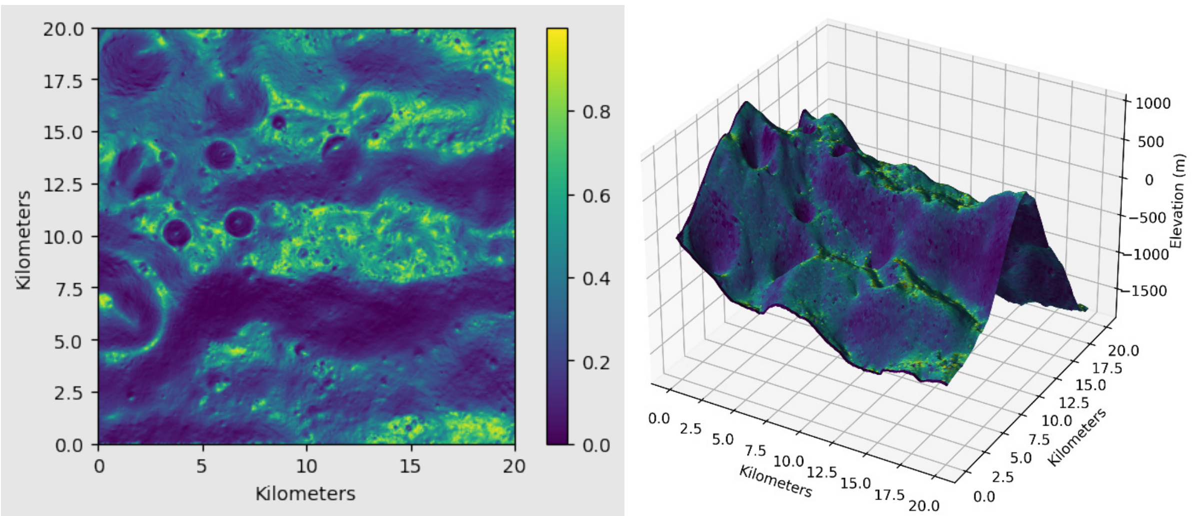

Figure 5: Left: A two-dimensional map of accessibility for Site01, normalized (where one is optimum). Right: The two-dimensional accessibility map projected onto the three-dimensional surface of Site01 (Note the vertical axis has been set to meters in order to accentuate topology for viewing purposes).

5 DISCUSSION AND RECOMMENDATIONS

The system proposed in Chapter 4 provides an AI and ML capability to optimize the location of a future lunar outpost. This chapter discusses the legal, cultural and ethical implications of the proposed system and explores opportunities for further development and future applications of the system.

5.1 LEGAL, CULTURAL AND ETHICAL CONSIDERATIONS

The subjective, complex, and qualitative nature of ethical, cultural, and legal decision-making means AI and ML systems are poorly suited to the optimization of these aspects of a lunar outpost location. However, AI- and ML-generated insights delivered by the proposed system can complement traditional ethical, cultural and legal analysis, helping human decision-makers make well-informed decisions about risk management and heritage protection.

5.1.1 Create a new normative framework for the exploration and use of celestial bodies

The operation of the proposed system should be backed by a permissive normative and regulatory environment. The current normative framework governing space needs to be enhanced to: ensure that it supports the new ways in which humans access and use the Moon; formalize emerging behavioral norms; and contribute to the development of customary international law in this area. In the current geopolitical climate, it would be exceptionally difficult to achieve a 'mega treaty' (Rajagopalan, 2021), but enhancement can be achieved through:

- the creation of multilateral agreements or a series of bilateral agreements that reflect a hub-and-spoke model (as in the case of the Artemis Accords);
- the development of a robust risk management strategy; and
- coordinated regulation of AI and ML capabilities.

Any entity establishing a lunar outpost should develop a robust risk management strategy (based on a benefits and risks analysis) at the international and domestic level. The risk management strategy should address how to employ AI and ML safely; ensuring its use is compliant with legal obligations; and security aspects (including physical security of the capability and mitigations to ensure the integrity of the datasets is not compromised). The risk assessment can inform the development of a normative framework, particularly in circumstances where the risk assessment identifies tasks which cannot be mitigated to acceptable levels.

A new review regime should be created (akin to the regime required by Article 36 of Additional Protocol I of the Geneva Convention) to review all new and modified AI and ML capabilities, like the one proposed in this report, to ensure that they can be used in compliance with international law, and national policies.

To ensure the proper use of the proposed AI and ML capability, it should be employed within a responsible chain of human control. Further regulation at the international and national level is required to ensure that states, individuals and companies associated with AI and ML use are held accountable for breaches of law.

Without regulatory reforms the gap between the provisions in the space treaties and the realities of human activity in space will only widen. It is therefore recommended that the international community, led by the UN COPUOS, discuss the normative framework (including a legal gap analysis) in order to identify areas requiring reform.

5.1.2 Use AI and ML to support risk management

The proposed system has the potential to deliver a location optimization capability that supports risk management by optimizing locations for crew safety. Travelling to space has an impact on the mental and physiological health of the crew due to exposure to radiation, weightlessness, sleep disruption, disorientation, and gravitational shifts (Cooper, 2016). The proposed system provides a tool that can help decision-makers understand the risk posed by a given location's exposure to radiation and terrain features. From an ethical perspective, further consideration is required as to the risk tolerance levels associated with the deployment of humans on the Moon. Mitigating the risk of adverse health effects to astronauts is ethically, as well as operationally, beneficial.

5.1.3 Preserve and manage AI and ML systems used in space exploration as cultural artifacts

The use of the proposed AI and ML system to optimize location specifications for the first human outpost would transform it into an important cultural artifact. The datasets, logs, code, algorithms, servers, and histories associated with the optimization of our first off-Earth permanent settlement would become the shared heritage of humanity and should be preserved, archived, and managed in the same manner as equivalent technological cultural objects (Swade, 2002). Organizations using the system to undertake future settlement activities in space should incorporate these guidelines and curatorship requirements into long-term mission planning as appropriate, parallel to curatorship considerations for physical artifacts.

5.2 FUTURE APPLICATIONS OF THE PROPOSED SYSTEM

5.2.1 Minimize impacts on existing sites of cultural significance in space

When considering locations for a future human outpost, state and non-state actors should minimize the impact on existing sites of historical significance, for example, the Apollo 11 landing site on the Moon (O'Leary, 2009, pp.757-780; O'Leary, et al., 2000). Future system requirements for the proposed AI and ML system could include preserving sites and objects located on the Moon that have cultural, aesthetic, or spiritual significance if a dataset identifying these sites can be created (The Venice Charter, 1964; Australia ICOMOS Burra Charter, 2013). AI and ML can also be applied to remote sensing products to monitor changes to the historical sites in the solar system over time, but they are not well suited for qualitative assessments of what such changes mean for the social and cultural value of the first human outpost.

5.2.2 Use commercialized AI-as-a-Service for future off-world outposts

Commercialized NASA innovations and applications generate an estimated annual revenue ranging from $100 million up to $1 billion USD (The Tauri Group, 2013). These applications include commercialized technologies in life sciences, telecommunications, and educational tools. The McKinsey Global Institute predicts that the use of AI tools could yield a worldwide economic output of $13 trillion USD by 2030 (Lins, et al., 2021). This suggests the potential to translate the proposed AI and ML technologies from a lunar outpost into commercialized products, generating significant revenue.

AI and ML has been successfully used in the construction sector to increase competitiveness and profitability through optimized building, including location, material choice and workflow management (Pham, Hong and Tran, 2021). This report suggests using AI and ML tools to optimize lunar base location, which can be translated to create AI as a service (AIaaS) for other lunar bases and planets.

Developing AI models from specific and detailed data, such as lunar conditions, is a lengthy and expensive process (Haenlein and Kaplan, 2019). AIaaS, however, would allow adopters to configure models to their particular requirements without the expense or maintenance of the original algorithms (Lins, et al., 2021). The commercialization of lunar data through this AI tool would be able to extend novel scientific research while simultaneously providing financial capital.

5.2.3 Use lunar outpost data to create a simulation

Over the past decade, video games have grown in popularity, with AI personalization of gaming experiences increasingly being incorporated (Akter, et al., 2020). Research has found games support stimulating student engagement, learning and leadership (Shi, et al., 2019) For JAXA's Lunar Orbiter Kaguya (SELENE) missions, lunar data was visualized for public outreach and education (Okumura, et al., 2008). Creation of a digital twin simulation of a lunar outpost using data from the AI and ML system, converted into a gaming experience personalized by ML to the individual player, would be a powerful application for public engagement, education, and revenue.

> ***"When technology works on a personal level, it creates an enduring bond with the users. Furthermore, when marketers tap into such a bond, the potential for customer value creation is enormous." (Kumar, et al., 2019).***

5.2.4 Use of AI and ML tool for analysis of subsurface structures

The proposed AI and ML system for optimizing outpost location could be enhanced in the future by including remote identification of subsurface structures such as lava tubes and pit craters and assessing important properties such as depth, morphology, and roof thickness. This information will be highly relevant for the feasibility assessment and future design of human habitats and warehouse storages in lava tubes (Hong, Yi and Kim, 2014). Transfer learning could be applied to adapt terrestrial data to the Moon environment, allowing for better generalization of related, but different, lunar structures (Caruana, 1997).

5.2.5 Adapt AI and ML tool for optimization of locations of missions to other celestial bodies

The proposed AI and ML system could be applied to other planetary environments. As many of the same conditions must be maintained and some similar challenges must be overcome, systems can be used with minimal changes. The learning component of AI and ML means that the technologies are highly transferable: a system built to optimize a lunar outpost can be reapplied to Mars or other celestial bodies as long as appropriate datasets are available.

The system presented in Chapter 4 can be applied to any environment where sufficient data exists to satisfy the user-defined location requirements. Where a complete dataset does not exist for the target location, the framework can operate at a reduced capacity and provide a lower accuracy estimate. The modular design of the system ensures it is as flexible to environmental changes as possible, meaning users can adapt the framework to reflect unique conditions of an environment.

6 ROADMAP

The roadmap provides direction on next steps to achieve the main goal of this project: optimizing the first sustainable human lunar outpost. The roadmap is structured in a way that encompasses current AI and ML capabilities and their use in space exploration, the knowledge gaps identified through the review of the existing literature, and the proposed recommendations from legal, ethical, and humanities perspectives. The following subsections describe the components of the roadmap in Figure 7.

6.1 LAW AND ETHICS

Legal and ethical frameworks identified in this report affect activities across the entire roadmap. A permissive normative and regulatory framework will need to be established and maintained, and public and private organizations establishing the outpost will need to develop and adhere to appropriate risk management strategies.

6.2 ENABLING TECHNOLOGIES

Identification of technologies that will form the basis for future remote lunar data collection, including cis-lunar orbit spacecraft and surface rovers, with the purpose of creating rich datasets that the proposed AI and ML system can use, as well as a full-scale iteration of the proposed AI system. Chapter 3 and Appendix A identify types of data that will need to be collected for the optimization of a lunar outpost.

6.3 LUNAR SURVEYING

Once the enabling technologies have been developed, remote sensing and surface rover missions actively collect the data required for analysis, including space weather, lunar terrain, radiation levels, surface and sub-surface composition, and solar exposure. Chapter 3 and Appendix A propose remote sensing and rover missions needed to close identified knowledge gaps.

Preparation of data forms a vital step in training AI and ML algorithms. Lunar surveying datasets will likely require augmentation with terrestrial data to account for limited datasets in the lunar environment. Collated datasets underpin the performance and extensibility of the AI and ML algorithms designed to control vital operational and design aspects of the lunar settlement. Testing the efficacy of the AI and ML algorithms prior to deployment is essential.

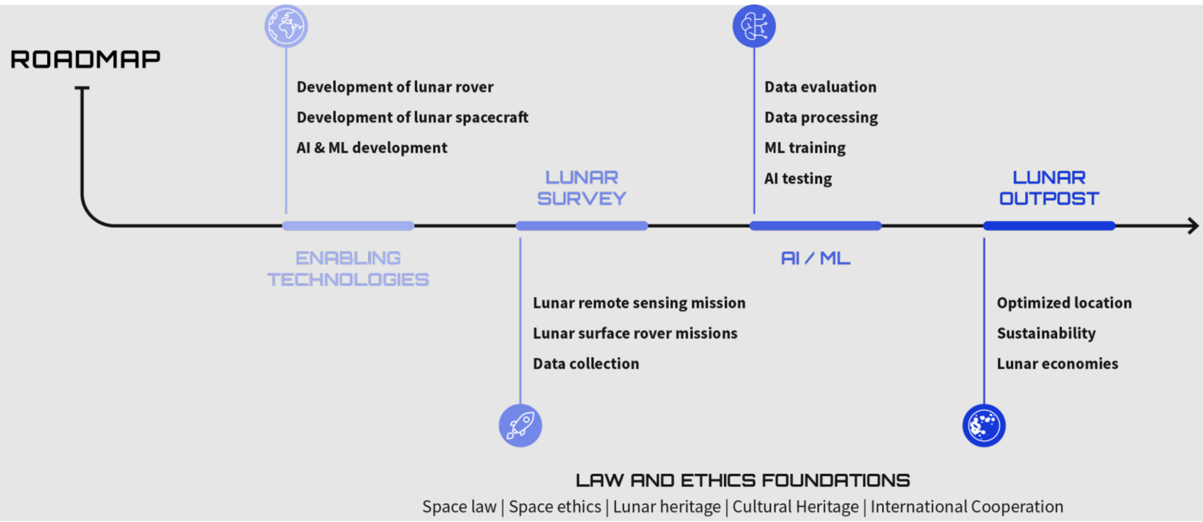

Figure 6: Roadmap for the implementation of the proposed AI and ML system

7 CONCLUSION

The establishment of humanity's first off-planet outpost will be a defining moment in the history of our species. The success or failure of this enterprise will determine the future of crewed spaceflight endeavours for generations to come and is a crucial step towards humanity becoming a multi-planetary species.

This report has demonstrated the feasibility of using AI and ML to optimize some specifications of a lunar outpost and provided interdisciplinary perspectives on how these tools can be used appropriately.

The report undertook an interdisciplinary approach to addressing how AI and ML can be used to optimize lunar outpost specifications, focusing on seven disciplines: space applications, engineering; management and business; human performance; science; humanities; and policy and law. Our initial broad investigations of this issue lead to a narrowed focus on using AI and ML to optimize the location of a lunar outpost, addressing five specifications: solar exposure; terrain access; scientific diversity; minimization of environmental impacts on human crews; and access to resources. An AI and ML interface was then developed that uses lunar data, human requirements, and anticipated concerns to determine the optimal location for an outpost that meets stated necessary conditions.

The outcome was a proposed modular, interconnected system that can assist in the process of selecting the optimum location for a lunar outpost. The system can integrate data from multiple available lunar data sets, including satellite data and rover measurements. Relevant large-scale datasets from Earth can also be employed as analogs to enhance decision-making. Mathematical rules are defined for each requirement and are applied to the data collected for different regions of the Moon. These rules are the key drivers of the AI decision process and are employed to distinguish regions suitable for a human outpost from those not compatible with our mission requirements.

The efficacy of the system is demonstrated by a prototype model, with a narrow focus on the terrain accessibility specification for a lunar outpost location at the lunar south pole. The prototype system successfully produced optimized mapping and 3D visualization data of locations with suitable terrain accessibility.

The report also provided further discussion of the legal, ethical and cultural implications of implementing the proposed AI and ML system, as well as possible future applications of the system that can form the basis for further investigation.

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9 APPENDIX

9.1 KNOWLEDGE GAPS RELATING TO SELECTED SPECIFICATIONS

9.1.1 Optimizing Lunar Outpost Location for Solar Exposure

Solar energetic particle (SEP) radiation is a small fraction of the radiation encountered on the Moon. UV radiation, solar wind, and galactic cosmic radiation (GCR) with heavy ions may play a role in the alteration and long-term preservation of organic matter. Degradation of organic compounds by solar particle radiation should be higher now than in the early solar system's formation because of changes in solar wind and radiation fluxes. According to Matthewman, et al. (2016), a preservation strategy that minimizes the time organic meteoritic material is exposed to radiation reduces the chance of degradation.

Defining the optimal location for a lunar outpost requires extensive consideration of solar exposure. Solar exposure significantly influences suitability for scientific observation, positioning and design of power systems, and thermal regulation of the habitat and associated structures. At present, the optimization of these aspects is limited by the resolution of illumination, slope, and roughness data. This knowledge gap will be narrowed as future probe technology provides higher resolution data, thereby offering improved insight into location suitability. Current technology, such as the Lunar Prospector Orbiter Narrow Angle Cameras (NAC), have produced images revealing illuminated massifs and crater rims; areas which previous models have predicted to be shadowed. Conversely, images also revealed regions in shadow which models previously predicted to be illuminated (Speyerer and Robinson, 2013).

Discovering small peaks on the lunar surface near the south pole allows for maximization of continuous solar exposure, whilst reducing long periods of shadow. NASA's Lunar Reconnaissance Orbiter mission characterized the illumination environment of the Moon's polar regions using LOLA. The topography images found that small elevations in altitude increased the amount of time the region was illuminated. (Mazarico, et al., 2011).

9.1.2 Optimizing Lunar Outpost Location for Terrain Access

Terrain traversability estimation is integral to autonomous lunar surface exploration, which will be necessary as communication delays will limit the level of direct intervention a vehicle can receive (Paton, et al., 2020). Traversability estimation accurately predicts factors such as a planetary rover's attitude in rocky terrain and the location of surrounding obstacles, to generate the safest path to take between two points.

Path planning such as this has been demonstrated on Earth, however constraints such as not considering the rover's response to speed variations, mechanical properties of the Lunar regolith, only evaluating linear trajectories, and lack of integration into path planning and following subsystems indicate that more work is needed to improve this technique (Ho, Peynot and Sakkarieh, 2016).

Moreover, to achieve satisfactory performance multiple learning inputs are necessary to predict terrain traversability. These inputs are often in the form of new datasets and sensors, can be analyzed using analysis of variance techniques among others. The most meaningful input data for terrain traversability is terrain geometry, as reflected by the rover's attitude and configuration (Ho, Peynot and Sakkarieh, 2015). It is necessary for any vehicle acting autonomously to have the fullest possible understanding of its surroundings.

The Lunar Reconnaissance Orbiter (LRO) Camera has been used to capture multi-temporal, high-resolution imaging data of lunar regions (Speyerer and Robinson, 2013). The image datasets are utilized to illuminate and analyze shadowed regions of the lunar surface. The narrow and wide-angle cameras can generate high resolution maps for terrain access under different lighting conditions.

The representations of the terrain immediately surrounding a rover, which are assumed to largely be generated by the rover's exteroceptive sensors, are frequently deficient for planning an entire journey because of limitations and sensor constraints. Additionally, during terrain crossing, the rover-terrain communication can cause territory deformity in these representations, which may significantly change the difficulty of passing on lunar deformation surface (Ho, Peynot and Sakkarieh, 2016).

A synthesis of the available datasets related to lunar topology and geological information as well as onboard sensing will benefit the overall approximation of terrain accessibility and allow safer passage for an autonomous vehicle. Initial surface missions to gather baseline data on the best means of traversing certain regions will enable the establishment of transportation routes into the future.

9.1.3 Optimizing lunar outpost location for access to diverse sites of scientific interest

Lunar missions from the past several decades, such as NASA's Lunar Prospector, LRO, and Moon Mineralogy Mapper, have contributed significantly to our understanding of the Moon's scientific characteristics. These, along with other remote sensing lunar missions and samples collected on the surface by Apollo astronauts, have provided researchers with data to reach a range of conclusions regarding surface features; elemental abundances including the presence of water; neutron flux; gravity fields; magnetic fields; and regolith composition (Grun, Horanyi and Sternovsky, 2011; Shkuratov and Bondarenko, 2001 and Zhang, et al., 2014).

While remote sensing data can provide extensive insight into lunar science, it has limitations and biases. Remote sensing data is currently limited by the orbits and altitudes of the spacecraft when it carries out its data collection. To mitigate this, remote sensing data from one mission is often complemented with the data from another mission, as is demonstrated by Prettyman (2014). Remote sensing data is also complemented with lunar samples collected on the Apollo missions and lunar meteorites to confirm conclusions such as the presence of water (Hiesinger and Jaumann, 2014).

Researchers have been able to use currently available data to provide recommendations for science-rich lunar landing sites (Flahaut, et al., 2012), however, there are still significant gaps remaining (Flahaut, et al., 2012 and Sauro, et al., 2020). A significant knowledge gap exists for underground and subsurface lunar characteristics and features. Whilst remote sensing observations can indicate possible underground and subsurface structures, further information and confirmation is limited with current remote sensing capabilities. A specific example includes lava tubes structures beneath the lunar surface. Chappaz, et al., (2017) suggests there is strong evidence from the NASA gravity recovery and interior laboratory mission's data for empty lava tubes on the Moon. Imagery from the LRO narrow angle camera on the LRO reveals holes in the surface that have been characterised as "skylights" to underground caves or lava tubes (Haruyama, et al., 2012 and Sauro, et al., 2020).

To better understand the characteristics of lunar lava tubes and pit craters, research groups have made use of data from analogue terrestrial structures which, although originating from different processes, present similar topographical characteristics (Hong, Yi and Kim, 2014 and Sauro, et al., 2020). The addition of "ground truth data" would provide scientists with significant details of the lava tubes and the potential opportunities they, and other underground structures, may pose for human exploration and our knowledge of the solar system (Sauro, et al., 2020).

9.1.4 Optimizing lunar outpost location to minimize environmental impacts on crew health

One of the most critical aspects in the lunar outpost is the wellbeing of the crew it is intended to house. Without the human component there is no outpost, merely an oversized robotic mission. Adding the human dimension to space exploration vastly increases mission complexity, and it is appropriate that attention should focus on optimizing the performance of the mission's human element in order to provide the greatest return on this investment. NASA's Human Research Program (HRP) has identified 199 knowledge gaps that need to be addressed to characterize and mitigate risks to astronaut health and performance (Human Research Roadmap, 2022).

When establishing an outpost, the level of functionality must be decided. This may vary from the merely 'survivable', providing the bare essentials necessary to sustain a small team at a given location for the duration required to complete a specific task; through the 'functional', providing larger teams the ability to maintain a continuous presence in one location on a rotating basis; to the 'optimal', which potentially allows for permanent habitation of the site. The hierarchy of needs for human existence extends from air at one extreme, to aesthetics at the other – and the level of functionality chosen will determine both the design philosophy and the scope of works required to realize the project.

Of the seven environmental factors identified as impacting human performance on the Moon (radiation, gravity, temperature, pressure, distance, diurnal cycle, and dust), three have a major location-specific component (radiation, temperature, and diurnal cycle) and are thus potential targets for AI/ML-assisted optimization of outpost location. Of these, radiation is the most significant threat to long-term habitability. Most current studies on radiation relate to the prevention, by using mass shielding techniques such as aluminum, water, and regolith to minimize the impact of radiation on astronauts (Cooper, 2016).

In-depth geographical studies of the lunar surface, known as selenography, have also been conducted to identify a variety of data surrounding topography and geology (Tillotson, 2019). However, there are knowledge gaps in the application of these results to radiation minimization. Based on current knowledge, the following areas have been identified as having the greatest impact on surface radiation.

- Latitude – the amount of solar radiation per square meter decreases significantly at higher latitudes owing to the obliquity of the lunar surface relative to the incoming radiation, in accordance with simple geometric principles. (Williams, et al., 2017)
- Local topography – the 'shadowing' effect of nearby elevated terrain has the capacity to influence both solar and galactic cosmic radiation flux at a lunar outpost. This is particularly true at the Poles, where there are craters whose interiors are never exposed to daylight. Even away from the Poles, however, positioning an outpost within a crater will reduce the ambient radiation by raising the horizon in all directions and thus reducing exposure to the isotropic GCR and the Sun at low elevations (Cooper, 2016).
- Local geology – an in-depth knowledge of the sub-surface composition of candidate sites for a lunar outpost is essential. Details such as the water content are important not just for the purposes of human consumption and the manufacture of breathing gas and rocket fuel, but also because of water's value for mass shielding of an outpost against radiation. Additionally, any local magnetic fields need to be mapped to determine their value in potential active shielding against incoming radiation. There is evidence that surface features known as lunar

swirls are due to local magnetic anomalies diverting incoming charged particles along magnetic field lines, preferentially shielding some areas to the detriment of others (Blewett, et al., 2020).

To determine a conclusive map of radiation exposure on the lunar surface, the following techniques can be implemented to gather accurate, area-specific data on the following areas:

Surface measurements of local magnetic fields and their effect on charged particle influx. Remote sensing missions like the Lunar Reconnaissance Orbiter (LRO) have captured valuable information about lunar radiation, however there is very limited data on active radiation dose measurements from the surface of the Moon. The first example of this was the Apollo astronauts who carried dosimeters on their missions. This provided radiation dose data with significantly improved accuracy from previous data. The only time-resolved lunar-based radiation detection is from the Chang'E 4 lander. While Chang'E is a valuable tool to measure radiation on the lunar surface, it is stationary, which means it cannot map additional locations. Developing a remotely or AI-controlled rover which would be able to map locations that have been identified by remote sensing data would be valuable in ensuring the accuracy of previously collated data. Artificial Intelligence can also be implemented to allow the rover to traverse the lunar surface in an efficient manner and collate the collected data into a user-friendly map (Zhang, et al., 2020).

Surface sampling of local geology is also desirable to verify and calibrate data acquired by remote sensing. The robotic rover undertaking the magnetic field and radiation level surveys discussed above should, ideally, be equipped to perform this function too.

These datasets can then be combined with high-definition remote sensing data (such as topography and geology) in a geographic information system to determine the optimal location for a lunar outpost from a human radiation exposure perspective. Different factors within the system will need to be weighted differently depending on the outpost's operational priorities, and AI and ML tools may be of value in optimizing its location. Ground truthing will be essential for the initial outpost but is expensive and time-consuming, and – as the human presence on the Moon expands – it is possible that machine learning will permit site selection from remote sensing data only.

With the development of advanced remote sensing technologies like NASA's LRO (2022), there have been a variety of data captured to map the Moon's surface. For example, the LRO is designed to measure galactic and solar radiation on the Moon and has discovered a new radiation source from the reflection of cosmic rays from the Moon's surface. In addition, it can acquire stereo photographs to create 3D maps that allow a better understanding of the structure of the lunar surface. This includes creating high-resolution topographical and mineralogy maps of the Moon. LOLA is also used to obtain a more comprehensive understanding of the lunar topography, and can measure slopes, heights and depth of the surface with relative accuracy. Besides, laser altimeter observation can make up for the lack of lighting, ideal for mapping PSRs. (Riris, et al., 2017)

Individually, these instruments generate important data for studying and analyzing the lunar surface but are not conclusive from an operational perspective. For example, by combining techniques such as laser altimetry with viewing 3D maps and radiation measurements from the lunar surface it would be possible to define craters with the most coverage from local radioactive fields. To enhance this, Artificial intelligence can be used to create a model that overlaps and analyses all the different data for identifying the most habitable locations.

9.1.5 Optimizing sustainable lunar outpost location for resource access

Much work has been documented on the analysis of returned lunar samples, and on lunar regolith simulant. However, due to the limited volume of return samples and the high variability in available lunar simulant, adequately verifying the suitability of technologies for in-situ use poses a challenge to engineers (Simulant Working Group, 2010). Both water and oxygen have been identified as present on the Lunar surface and important resources for long-term Lunar operations (Wiechert, et al., 2001; Chen, et al., 2015).

Over the course of a lunar day, the amount of surface water can vary by 200 parts per million, and the upper meter of the regolith may contain an average of 1.2 1014 g of water (Li and Milliken, 2017). Samples from previous lunar missions have been analysed, and the various oxygen isotopes and their relative abundance in the samples has been previously determined with laser fluorination in a large, well-equipped laboratory (Wiechert, et al., 2001).

Replicating these results and documenting the necessary technological improvements required to extract oxygen in-situ will be necessary to utilise this lunar resource. Reports from planetary scientists from the University of Hawaii suggest that the abundance of water is extremely low within the trapped shadowy craters, and the extraction procedure could involve processing thousands of kilograms of lunar regolith to get 1 kilogram of water (Hsu, 2009). Several challenges occur as a result of this extraction process, including the heating element, which will be quite expensive in terms of power usage if not optimized through factors such as volume confinement via heated walls (Brisset, Miletich and Metzger, 2020). Also, the optimal extraction efficiency directly correlates to the ice content of the soil in order to determine the heating configuration (Brisset, Miletich and Metzger, 2020). As a result, detailed prospecting will be required to plan future ISRU activities on the lunar surface. Oxygen can be extracted from lunar regolith by thermochemical reduction or by extraction from ice deposits. For a feasible mining operation, a large area of deep ice is required. Even if the surface ice is stable, it is advisable to start mining at tens of centimeters or deeper. (Cannon and Britt, 2020).

The remote sensing data of the water ice available today is only of the surface. Further data of the depth of the ice is required. Impact gardening over time can affect the distribution of ice on the lunar surface hence younger reserves would be preferred for a sustainable outpost. For thermal mining of water ice, a rise in mining temperature increases the amount of water vapour collected but also causes the water vapour pressure to increase which can lead to system instability. In a study analysing the optimum temperature for mining, 220 Kelvin was identified as the most favourable for in-situ thermal mining (Song, et al., 2021).

Applications of machine learning and artificial intelligence may assist in future autonomous sample collection and processing operations, which may in time develop the systems necessary for sustainable large-scale in-situ resource utilization.

Using Artificial Intelligence and Machine Learning for Optimizing Space Mission Strategies

TEST CASE: OPTIMIZE LUNAR OUTPOST SPECIFICATIONS

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