Establishing Assessment Criteria for Intelligent Infusion of "Smart Systems" into a Space Habitat

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Deep-space habitats for future human exploration missions will require unprecedented levels of autonomy as Earth-reliance is reduced and self-sufficiency becomes increasingly necessary. Identifying the critical functions needed to support the crew when they are resident, and alternatively to keep the vehicle operational during potential uninhabited periods, is a first step toward assessing how to best meet these essential needs in a safe and efficient manner. From this functional framework, subsystems can be defined and associated operational tasks can then be allocated to either humans or automated systems, which can be accomplished via onboard or ground means. Incorporating 'Smart Systems' into the design offers an additional option moving beyond traditional approaches. These include emergent technologies in autonomous systems, dense sensor populations, data science, machine learning, robotic maintenance, and on-board manufacturing. This paper provides a systematic overview of functionally-driven design and operational principles for self-reliant spacecraft with intermittent human habitation, and classifies broad categories of candidate smart technologies for consideration. From this framework, infusion of these emergent technologies will be systematically assessed to guide 'intelligent' implementation of smart systems in the design and operation of a deep space habitat.

Nomenclature

AI	=	Artificial Intelligence
ConOps	=	Concept of Operations
DRM	=	Design Reference Mission
ECLSS	=	Environmental Control and Life Support System
ESM	=	Equivalent System Mass
HOME	=	Habitats Optimized for Missions of Exploration
LEO	=	Low Earth Orbit
STRI	=	Space Technology Research Institute
TRL	=	Technology Readiness Level

I. Introduction

DEEP SPACE habitats for future human exploration missions beyond Low Earth Orbit (LEO) will require unprecedented levels of autonomy as Earth-reliance is reduced and self-sufficiency becomes increasingly necessary. This is accomplished through system design and analysis of accompanying operational activities. Spacecraft operations are typically performed a) manually by the crew, b) autonomously by the vehicle subsystems, including onboard robotics, c) via a ground team, or d) through some combination of the above by coordinated task assignments. Identifying the critical functions needed to support the crew when they are resident, and alternatively to keep the vehicle operational during potential uninhabited periods, is a first step toward assessing how to best meet these essential needs in a safe and efficient manner. The process of defining 'what' needs to be done and assessing alternatives for 'how' to best accomplish it can be evaluated by first developing a Design Reference Mission (DRM) that establishes the scope of the mission at a high level. From this functional framework, subsystems can be defined and decomposed into their associated operational tasks for allocation to either humans or automated systems, which can be accomplished via the various onboard and/or ground control means noted above.

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Advances in 'Smart Systems' (typically referred to in the broad context of Artificial Intelligence or AI) offer a novel option moving beyond the traditional operational approaches. These include emergent technologies such as autonomous systems, dense sensor populations, data science, machine learning, robotic maintenance, and on-board manufacturing. This paper provides a systematic overview of functionally-driven design and operational principles for establishing self-reliant spacecraft with intermittent human habitation, and describes and classifies candidate smart technologies for consideration. From this framework, infusion of these emergent technologies will be systematically assessed to guide 'intelligent' implementation of smart systems into the design and operation of a deep space habitat as part of a NASA 'SmartHab' Space Technology Research Institute (STRI) project called *Habitats Optimized for Missions of Exploration* (HOME).

II. Functional Design Philosophy

A Systems Engineering approach to space habitat design begins with defining the goals of the mission. We, however, are focused on design considerations relevant to generic deep space habitats, so have started by defining a notional Design Reference Mission (DRM) that is generically relevant to a wide range of human exploration missions. The Concept of Operations (ConOps) depicted in Figure 1 shows a high level sequence of mission phases that also takes into consideration periods where the crew is not present.

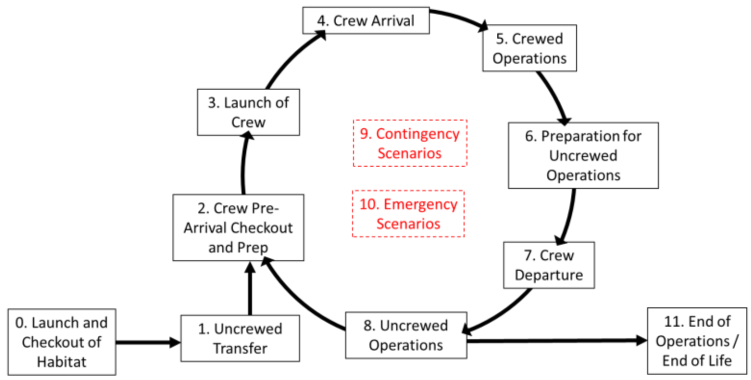

Figure 1. ConOps for a microgravity mission.

The fundamental tenets of human-rating are to *accommodate* the needs of the crew (what the vehicle provides), effectively *utilize* human capabilities to accomplish the mission objectives (operations), and *protect* the crewmembers, as well as ground teams and the uninvolved public, from hazardous events (risk mitigation). From these overarching guidelines, a set of non-negotiable requirements can be defined to meet the physiological needs of the crew (Environmental Control and Life Support System ECLSS) and satisfy the necessary physics of the mission (e.g., structural integrity, propulsive needs). Anything added beyond this minimum baseline must be justified by trade study in terms of cost, mass, complexity, etc. incurred to make the vehicle 'safer' or 'nicer' as risk mitigation strategies or operational enhancements, respectively. [1] Quantifying the 'benefits' associated with the various design choices, therefore, must be balanced against the 'costs' of implementation. In addition to the typical manual or automated options that are normally part of the trade space, we now add AI to the mix.

III. Concepts of Artificial Intelligence (AI)

What is artificial intelligence, or AI? The answer to this depends on who is asked. In the 1950s, Alan Turing posed the vague question "can a computing machine think?"[2] In October of 1950, Turing published a paper titled "Computing Machinery and Intelligence," in which he established the famous 'Turing Test.' This assesses the intelligence of a computer, suggesting that both a human and computer are asked a series of questions, and in order for a computer to be deemed intelligent, a human should not be able to distinguish the computer answer from a human answer.[3] The actual term 'artificial intelligence' was first famously coined at a conference in 1956 by John McCarthy.[4] At this conference, Noam Chomsky presented work on linguistics and human language in a presentation that was viewed by two pioneers of AI: Allen Newell and Herbert Simon. These two computer scientists also presented a paper at this conference on a computer program that could prove theorems in propositional logic.[5] The blending of these fields is thought to have led to the birth of cognitive science, and as a result this overlap of human experimental psychology, theoretical linguistics, and computer simulation is critical to our understanding and definitions of AI. Although the fundamental concepts of AI have been postulated for decades, as time has gone on it has become increasingly clear that there are further classifications of AI that must be implemented.

Although there is not a formal consensus of what Artificial Intelligence is across the literature, the definition can be broken down into different categories. A possible framework for this breaks down AI into categories of Thinking Humanly, Acting Humanly, Thinking Rationally, and Acting Rationally, as displayed in Table 1.[6] This method of understanding AI based on corresponding capabilities and examples of human and rational thought served as a foundation for how to incorporate and understand AI in the scope of a deep space mission.

Table 1. Framework for AI Processing.

Thinking Humanly	**Thinking Rationally**
"The exciting new effort to make computers think . . . *machines with minds*, in the full and literal sense." (Haugeland, 1985) "[The automation of] activities that we associate with human thinking, activities such as decision-making, problem solving, learning . . ." (Bellman, 1978)	"The study of mental faculties through the use of computational models." (Charniak and McDermott, 1985) "The study of the computations that make it possible to perceive, reason, and act." (Winston, 1992)
Acting Humanly	**Acting Rationally**
"The art of creating machines that perform functions that require intelligence when performed by people." (Kurzweil, 1990) "The study of how to make computers do things at which, at the moment, people are better." (Rich and Knight, 1991)	"Computational Intelligence is the study of the design of intelligent agents." (Poole *et al.*, 1998) "AI . . . is concerned with intelligent behavior in artifacts." (Nilsson, 1998)

Before considering how to incorporate AI into a space habitat, a review of the range of capabilities typically identified under the broad umbrella of Smart Systems was conducted, both from a historical perspective, as described above, and through assessing current trends in terrestrial applications, as many Smart Systems rely on advances in AI to differentiate themselves from more contemporary technology. From a survey of the literature starting with early seminal works by Turing, Newell, and Simon, and continuing up through modern research areas, a working framework defining different concepts of AI with increasing complexity was developed, as depicted in Table 2 below.

Table 2. Concepts of Artificial Intelligence / Smart System Applications

Category	**Examples**
Data Processing	Basic computer, Machine Learning, Deep Learning, Predictive analytics,[7,8] Neural Net, 'Big Data'
Human Interaction	Voice recognition,[9,10] Speech, Vision, Immersive environments, Robot teams[11]
Human Assistance	Self driving cars,[12,13] Auto-pilot, Siri/Alexa, 'Smart' exoskeleton, Bionics,[14] 'Ironman,' 'R2D2'
Bio/Human-Mimicry (*Embodiment*)	Anthropometric (or other life form), NASA Robonaut, MIT Cheetah, Japanese Robot 'Erica,' 'Cyborg,' 'iRobot,' 'C3PO,' Adaptive autonomy[15]
Meta-Human	Human exceedance, IBM's 'Big Blue,' Recent computer-to-computer AI language acceleration event (see Facebook 'Bob and Alice'), the 'singularity'

The five categories indicated in Table 2 group the various AI applications into a somewhat increasingly complex hierarchy of Smart Systems. These categories represent a range of capabilities that can be considered for enhancing the safety, as well as improving robustness and/or operability, of a space habitat. After developing this working framework of AI, a similar process was followed to better define Smart Systems. One philosophical definition of a 'smart system' is "an inherent ability to gather information on its operating environment or history, to process that information in order to draw intelligent inferences from it and to act on those inferences by changing its characteristics in an advantageous manner."[16] These frameworks serve to constrain the problem and define a set of operating parameters to reference when determining which concepts of AI are advantageous for a deep space mission.

A. Artificial Intelligence (AI) Crew Performance Enhancement Methods

AI can be used to improve crew performance in myriad ways, including advancements in task scheduling capabilities, allocating real time adjustments, and enhanced performance monitoring, to list a few. Planning flight activities constitutes large amounts of time for ground teams to analyze activities and create schedules, with updates frequently required to avoid overburdening the crew and impacting their ability to carry out the tasks. The Mir/ Progress collision in June 1997, for example, was attributed to a combination of operational factors, including crew fatigue and stress, combined with a lack of docking telemetry data. The Shuttle program incorporated very full crew schedules that were choreographed in advance and still modified daily. Current schedules on the ISS give the crew more flexibility in completing specified tasks, but optimal workloads remain unclear. By using an AI system to create and modify crew schedules during the mission, crew efficiency could be optimized. Considerations for the algorithm could include an individual's preference for certain tasks, as well as her/his individual speed and efficiency at a certain task. Inputs for the algorithm might include how the completion time of scheduled tasks are improved or negatively affected due to different daily parameters, such as amount of sleep, exercise, or food intake per crewmember. Additionally, a smart system could be used to monitor facial cues during these tasks to detect stress levels, indicating which tasks may be more taxing than others for crew.[17] An algorithm of this nature could create new daily schedules for the crew, and at the end of each day or task the crew would inform the algorithm of their feedback regarding the current schedule, which could be used to continually improve the schedule. This type of scheduling algorithm could be particularly useful during deep space missions, seeing as there has been little to no data collected from these types of missions and the crew will be experiencing long lag-times with ground control. It is unclear whether current scheduling regimes will be efficient, so a live updating system that creates modifications quickly could be highly useful on a mission of this type.

There are a number of ways in which artificial intelligence is being incorporated into the medical industry. Perhaps most relevant is a system that can monitor individual crew health. A deep space flight on the scale of a Mars mission has not been attempted before. It is unclear what the psychological effects may be from a long trip of this type. The close proximity to other crew members, limited communication, packaged foods, as well as the sheer distance from Earth could all potentially affect the mental health of the crew.[18] Currently, the ability to monitor the psychological health of the crew relies heavily on ground control personnel to monitor the data and communicate with crew members.[19] An AI system could monitor these potential changes. This could consist of a system that monitors facial expressions and language as well as specific vocal cues (intonation, expression, emotion) in order to detect any adverse changes during a long term mission.[20,21] There is no guarantee that a mental health professional will be on board, so this type of system could prove to be highly valuable. Taking on a new role within a group can present recategorization induction from an ingroup identity model, which is suggested as a potential intervention method if needed on a long term mission .[22] Electronic skin, or E-skin, is a developing technology that intends to imitate human skin and improve sensing capabilities. Unprecedented medical detection could be accomplished with e-skin that is created to be far more sensitive than human skin. Human skin functions primarily as a mechanical force sensor. E-skin in the future could be enhanced with biological or chemical sensors to target different liquid or gas media using electronic noses or tongues.[23] These sensors could be implemented in a deep space mission to record individual crew health in a highly individualistic manner with personalized details for each unique crewmember. Additional medical improvements include smart medical systems that can measure real-time physiological changes using near infrared spectroscopy to directly analyze blood and tissue parameters. These smart systems limit the necessity of drawing blood, and reliance on direct contact with a physician during flight.[24]

The applications discussed in this review are not all-inclusive, but represent different aspects of the seemingly endless opportunities for improvements in long term spaceflights with incorporation of Smart Systems. The options discussed are some of the most relevant and promising for the current time and capabilities.

B. Artificial Intelligence (AI) Risk Mitigation Strategies

With the intent of mitigating risks, AI embedded into space habitats can be a valuable asset in lowering the occurrence or severity of a risk. The ability to process vast amounts of data, recognize system performance trends or predict degraded performance of subsystems ahead of time can build an enticing argument for the implementation of smart systems deeply into the systems architecture. Overall, increasing the vehicles self-sufficiency and self-awareness is beneficial but requires a higher interconnectivity of systems.

1. Risk Acceptance

Risk Acceptance is the strategy of acknowledging that a specific risk exists but making the conscious decision to not mitigate it. The decision strategy is influenced by the findings in the Failure Mode and Effects Analysis (FMEA) and contrasting in terms of a corresponding cost/benefit analysis. Those FMEA's are mostly created during the design phase of a system and are therefore based on assumption at that stage. It has been demonstrated that data mining techniques can be used to evaluate the accuracy of a FMEA. Subsequently, with sufficient real-time and historical data, proper fault-isolation can be performed.[25] Consequently, updating the severity and likelihood values in the FMEA and risk matrix can result in the optimized selection of risk mitigation strategies.

2. Risk Avoidance

In contrast to risk acceptance is risk avoidance. When a risk with a high severity also has a high likelihood of occurring, the risk should be avoided even at a high cost to avoid crew or vehicle loss. Space exploration is motivated by our desire to reach destinations unknown. Hence, future crews and space habitat will need to endure foreign unfamiliar environments. By understanding which combination of circumstances in the unfamiliar environment can lead to hazardous situations is from upmost importance. Utilizing AI concepts (neural networks and deep-learning), subject-matter-expert knowledge, and historical data can help discover these "unknown unknowns" and quantify them. With the new set of hazardous scenarios for the new environment, decisions regarding which avoidance strategies can be formed.[26]

3. Risk Transfer

Instead of dealing with a specific risk, the responsibility can be shared across multiple systems or even handed off to another domain. Current space systems often rely on humans to make accurate decisions on anomalies, requiring the human operator to be highly skilled and trained. Nevertheless, operations on the International Space Station rely heavily on the crew and flight controllers to accurately diagnose anomalies. Future deep space missions will require the crew to be even more self-sufficient. However, the responsibility for accurate characterizations can be shared between crew and the space habitat. Artificial Neural Networks have shown to be effective in collaboration with human operators in diagnosing the health of equipment and predicting component failures.[27] Additionally, instead of constantly monitoring telemetry streams via human operators, various machine learning techniques have demonstrated their added value for space craft telemetry health monitoring.[28] By transferring the responsibility of complex tasks to smart systems, the crew schedule can be freed from these system health monitoring tasks.

4. Risk Reduction

Certain risks exceed the threshold for being acceptable but cannot be eliminated. Additionally, transferring the risk to another system is not possible. In this case, reducing the severity or occurrence of the risk is the appropriate action. One of those risks is crew injury and health during long duration missions. As mentioned in AI Crew performance enhancement methods, psychological health is important. Developing a mental condition can degrade overall crew performance and threaten mission success. Therefore, implementing a smart system that lowers the risk and/or supports early detection of depression, is valuable. Patients suffering from depressions react differently to positive or negative stimuli. Those differences can be observed via Electroencephalography (EEG) and visual responses. Previously, the evaluation of the EEG solely relied on manual analysis of the data. However, with the emergence of machine learning and neural networks, a greater set of data can be more thoroughly evaluated. The inclusion of neural networks is superior to machine learning data when evaluating EEG as it can include spatial information, in contrast to just time and frequency information.[29] The physical well-being of the crew is, of course, just as important as their mental health. To reduce the risk of a severe long-term damage caused by inadequate treatment capabilities, susceptibility inference networks could provide insight in selecting the optimal medical supplies. Such an approach requires – like many other AI systems – historical data input combined with expert knowledge.[30]

Even though many smart systems offer great potential improvements to self-sufficiency and self-awareness of the space habitat, the resulting increase in complexity cannot be neglected. Further research needs to be conducted to accurately evaluate the risk that these systems impose on the overall architecture and ultimately on the risk management process. Notably, the current extensive certification process for flight software shows that for future designs, a framework for incorporating smart systems and AI, where code can be rewritten in real time, needs to be established.

C. Artificial Intelligence (AI) Multi-Disciplinary Design Optimization Considerations

Just because something can be done, doesn't necessarily mean it should be done. In the context of evaluating the benefits of implementing AI into the vehicle design, the costs of doing so must also be factored in, including numerous parameters such as technology readiness level (TRL), added mass and/or complexity and resultant potential increased risks, logistical resupply needs, and development or programmatic risk.

Higdon and Klaus[31] characterized human spacecraft safety and operability through a minimum functionality design methodology. In this method, a lower bound for spacecraft mass is set using a set of essential functions that are coupled to a series single-string subsystems that are zero-fault tolerant. Here, the minimum functionality baseline is defined to ensure that the crew's physiological needs are met and that they arrive at the target destination, but does not include margin, dispersions, redundancy, or factor of safety. These are considered non-negotiable requirements, and can be defined as the combination of physics and physiology. The negotiable parameters are left open as the vehicle's trade space, and include safety and operability.

However, with the addition of Smart Systems and higher degrees of autonomy, this baseline spacecraft design must be expanded to support operations when crew is not present. The minimum functionality of the spacecraft is therefore split into two primary modes: crew present and crew absent. When the crew is present, the primary objective of the spacecraft will be to keep the crew alive, healthy, happy, and productive. When the crew is absent, the minimum functionality of the spacecraft will be such that the spacecraft is able to keep itself 'alive' and maintained for crew return.

Of course, additional cost-benefit analyses must be performed in order to ensure that the habitat is neither overdesigned nor unnecessarily complex. One of the simplest ways to evaluate different mission concepts or to compare different designs for the same mission is to compare their estimated costs. For aerospace systems, mass is a significant driver and proxy of cost. The Equivalent System Mass (ESM) is a cost-type metric based on allocated mass and is used to compare design decisions across the subsystems, but is most commonly used for life support systems.[32] However, this framework has also been extended to include astronaut diet as well as crew time.[33,34] It is important to note that the mass cost of additional crew time can vary depending on how much crew time is needed, and can be as large as the total mission mass or as small as additional consumables.

A comparable framework can be applied to Smart Systems; however, like the minimum functionality design, this method becomes significantly more complicated given the varying degrees of autonomy of the spacecraft. The framework for this analysis will require the characterization of the mass cost or savings of Smart Systems. For example, if the spacecraft self-diagnostics can identify a valve issue and repair the component before failure, this has the potential to save on resupply launch costs. This preemptive replacement in combination with optimized task scheduling and ECLSS consumable usage could lead to fewer and more optimized logistical resupply launches. Likewise, wearable health monitoring technology could lead to earlier diagnostics of crew injury or illness. Not only would this lead to lower rates of human factors-related failures, but it could better optimize crew time without overtaxing or overscheduling the crew.

One of the significant drawbacks of ESM is that it does not take into account the cost of redesign or architectural uncertainty. Battat et. al[35] defines the value proposition of technology investments and trade space of different deep space architectures given uncertainty. In order to analyze the ultimate payoff of each technology, it is critical to consider the TRL of each technology in conjunction with its contribution to the final spacecraft architecture. Ultimately, the operational risk of each additional Smart Technology must also be considered during the trade space exploration and design process.

While it is true that increased automation can lead to fewer accidents caused by human factors,[36,37] recent research has also shown decreased situational awareness during manual control following operations with high degrees of autonomy.[38] This poses a risk in contingency scenarios when the crew may be forced to take manual control during operations. It is also important to consider crew workload during extended stay onboard the spacecraft, when it is vital that they are neither under nor overloaded. Finding the balance between spacecraft self-sufficiency and crew independence within the levels of spacecraft autonomy will present a challenge that may vary between individuals onboard.

While the spacecraft must be self-sufficient and highly autonomous when the crew is absent, its primary function is to serve as a space habitat for humans, and thus the design must consider the needs of the crew above all else. In order to avoid an overdesigned and excessively costly vehicle, it is vital that each Smart Technology be critically examined and ultimately applied in an intelligent manner.

IV. Integrated Design Evaluation and Future Work

This paper represents a framework for concepts being evaluated as part of a NASA 'SmartHab' Space Technology Research Institute (STRI) project called *Habitats Optimized for Missions of Exploration* (HOME), led by The University of California, Davis, with numerous academic and industry partners participating, currently in its first year of operation of an intended 5 year total. The collective effort is aimed at identifying low Technology Readiness Level (TRL) innovative 'Smart System' solutions and assessing their infusion into a highly autonomous, deep space habitat for human crews. The team brings together expertise in human spaceflight and robotics, architecture and human factors, situational awareness, and smart architecture analysis and intervention. Emphasis is placed on evaluating cost/benefit impacts on vehicle life support and power subsystems, robotic applications, and human-machine interfaces. At the core of this effort is an underlying functionally-driven design philosophy, described here. It is aimed at defining success criteria and evaluating technologies to enable design of a self-reliant spacecraft with intermittent inhabitants.

Adding Smart Systems or AI solutions to the mix introduces novel options to the typical spacecraft design and operational trade space that can enable adaptive responses to evolving situations. As noted above, however, we hold that just because something can be done, doesn't necessarily mean it should unless it brings proven value to the end goal. With that in mind, we heed the sage and timeless advice of Abraham Maslow and William of Occam.

Maslow's hammer…
I suppose it is tempting, if the only tool you have is a hammer, to treat everything as if it were a nail.

Occam's razor…
The simplest solution is most likely the right one.

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