Development of the Crew State and Risk Model for Autonomous Biomedical Physiology State Monitoring and Prediction During Exploration Extravehicular Activities

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NASA has completed hundreds of microgravity spacewalks or extravehicular activities (EVA) over multiple decades and spaceflight programs. During the Apollo program, only 14 EVAs were conducted on the surface of the moon. The Artemis program aims to return to the moon for sustained human presence necessitating a new paradigm of surface EVA operations. Current microgravity EVAs and planned Artemis surface EVAs will rely on ground operations teams with near real-time communication (i.e., up to 10-15 seconds roundtrip delay); however, future Mars exploration will require crew to conduct EVAs at a full level of autonomy. The Crew State and Risk Model (CSRM) is being developed to enable autonomous biomedical support through monitoring and predicting of crew member physical and cognitive state during EVA.

The CSRM is a collection of seven core EVA physiology domains and are developed using empirical data modeling approaches. Each model subcomponent is developed and tested as crew member individualized models from EVA training analog data. The metabolic energy model estimates metabolic rate profiles from expected planetary EVA tasks. Levels of carbon dioxide (CO_2) inspired within a suit are estimated through the inspired CO_2 model. The human thermal regulation model predicts core body temperature and heat storage at < 3% error. The fatigue model estimates time and probability to physical exhaustion while EVA task performance predicts cognitive effectiveness and vigilance. Metabolic cost due to suited

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ambulation along an EVA path is generated using the traverse model. Hydration and nutrition status are predicted using the hydration, nutrition, and waste management model for readiness and recovery. Finally, the decompression sickness (DCS) model estimates risk and sensitivity to DCS based on mission profiles. Holistically, CSRM predicts key crew states through physiology determinants of performance between model interactions. This paper presents the architecture of the CSRM and details individual model development and proficiency in predictions of EVA physiology.

I. Introduction

NASA and the space community aim to return to the Moon with a sustained presence as part of the Artemis program. Through this endeavor, astronauts will be required to conduct spacewalks or extravehicular activities (EVA) in a new paradigm that includes an improved exploration capabilities that incorporate new ground to crew communication, EVA task operations, EVA biomedical support, and decision support tools. Historically, NASA and commercial partners have a strong record of completing spacewalks in the last 20 years through the International Space Station (ISS) platform. All of the ISS EVA operational components have been categorized with a highly regimented training, task planning, task execution, and communication infrastructure that guides crew from mission assignment to completing the actual EVA. In total, only 14 surface EVAs have been conducted on the Moon as part of the Apollo program which used limited technology and a highly differentiated training operational paradigm for EVA.[1] Furthermore, as NASA looks beyond the Moon for long-duration exploration class missions to Mars, crew will be required to operate at a level of autonomy not experienced before. As part of this strategic plan, the Moon to Mars program has both planned and built a framework of necessary advancements in the realm of exploration that are needed to achieve this autonomy allowing for successful science and exploration objectives to be achieved. As part of that strategic plan, there are a variety of stakeholders that have guided the exploration capabilities discussions of what a long duration spaceflight mission architecture and structure related to crew health and performance should prepare for to conduct exploration EVAs safely and reliably. Through this infrastructure, target focus areas and key capability gaps have been identified through the Environmental Control and Life Support System (ECLSS) – Crew Health and Performance (CHP) System Capabilities Leadership Team (SCLT). These core capabilities focus on Spacesuit Physiology & Performance, Crew Health and Countermeasures, Radiation, Exploration Medical Capabilities, Food Systems, and Earth-Independent Human Operations[2]. Recently, a CHP community of practice has released recommended research and technology development areas that are considered the highest priority CHP capabilities to enable human exploration on Mars. These are aligned with the SCLT roadmap capabilities and include Mars-duration food systems, Mars-duration effects on human physiology, risk mitigations for vehicle atmospheres, computational injury and anthropometric models, exploration exercise countermeasures, individual variability in responses to spaceflight, and sensorimotor countermeasures.[3] The objective of this community of practice is to evaluate and re-evaluate the capability needs as technologies mature and satisfy research and development progress towards conduct of long-duration spaceflight exploration operations.

To aid in achieving Earth-independent human spaceflight operations, new decision support tools are required to assist in real-time EVA task management and biomedical support. For current EVA operations on ISS, crew rely on near real-time communication with flight operations personnel in Mission Control to aid in troubleshooting, provide biomedical decision support, and guide through task procedural operations. When looking to early Artemis missions, this real-time support will still be achieved with minor latency; however, for sustained presence missions later in the Artemis campaign and looking to future Mars missions, these latency and communication delays will increase. Current worst-case Mars communication pathways approach 22 minutes one way, meaning crew would have a 44 minute communications delay during EVA operations in harsh if relying on Earth-based Mission Control for that support.[4] To address this concern, EVA decision support tools are being developed to aid in giving this autonomy in the realm of task management and interactions between Extravehicular (EV) and Intravehicular (IV) crew members to manage an EVA as an autonomous team, as illustrated in Figure 1. Development of the Personalized EVA and Informatics Decision Support (PersEIDS) system, currently being developed by the EVA and Environmental Physiology Laboratory (EEPL) at the NASA Johnson Space Center, focuses on this autonomous EVA paradigm in two phases. The first phase is compiling individual crew-specific data to build a personalized system to aid in EVA planning, operational training, pre-EVA readiness, path tracking, and consumable usage for a given EVA.[5] The second phase of this decision support system focuses on aiding the IVA crew member in EVA timeline tracking by providing biomedically-driven informatics related to EVA flight operational rules to track consumables, crew state, and task loading to enable crew to respond to operational events quickly, efficiently, and ensuring crew safety.

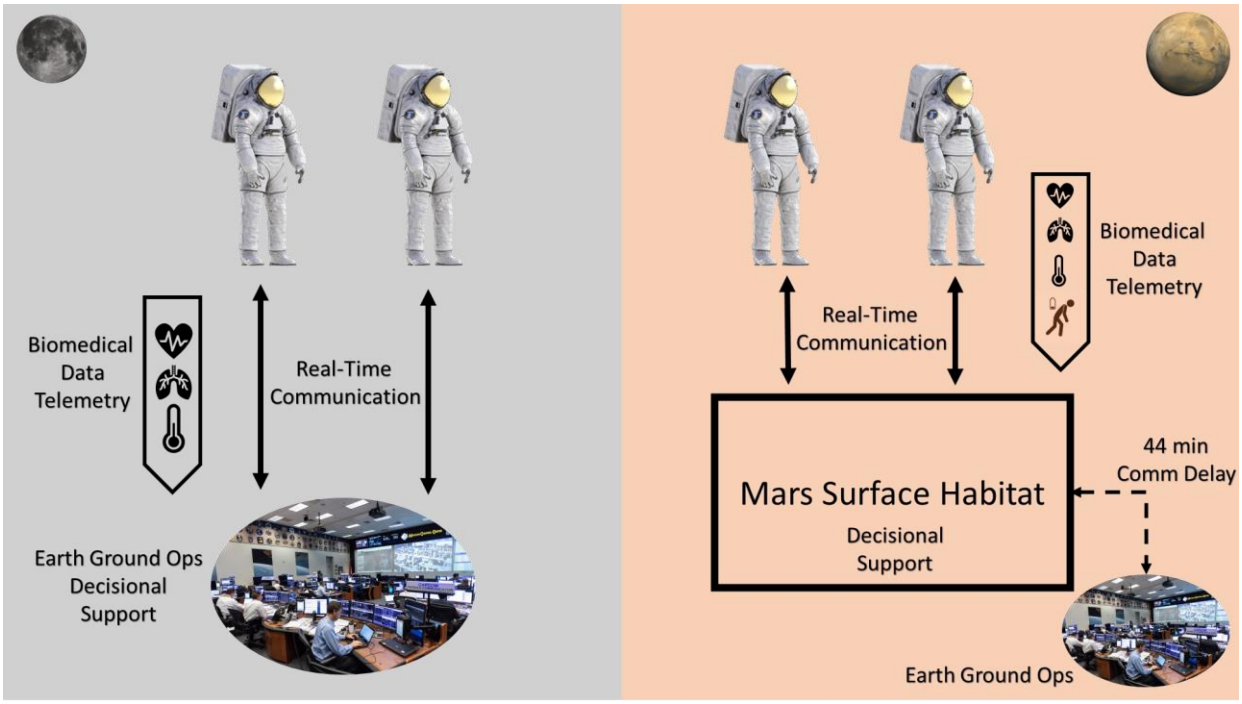


Figure 1. ***Conceptual operational communication difference between lunar and Martian EVAs:*** *During EVAs on the Moon, astronauts will be able to communicate to ground operations personnel in near real-time allowing for ground ops to make decisions using transferred biomedical data. Future EVAs on Mars will require a new paradigm of EVAs that will necessitate Earth independent operations. Crew will be required to make decisions with available*

A core component of the PersEIDS system is the Crew State and Risk Model (CSRM). This model suite is a collection of seven core physiology domains identified as essential to CHP and suited physiology operations to enable suit consumables tracking, crew safety, and tracking operational flight limits.[2,6,7] CSRM focuses on developing and curating individualized and personalized crew-specific physiology models derived from EVA analog training events and flight operational biomedical data. The individualized models can be updated then as new training events are achieved and aid in providing the specific crewmember with a personalized risk and readiness holistic model for aiding the entire mission team in guiding through autonomous EVA infrastructure. The seven cores include metabolic energy expenditure; in-suit inspired partial pressure of carbon dioxide (PiCO2); human thermal regulation; hydration, nutrition, and waste management (HNW); traverse as a metabolic cost to ambulation; physical and cognitive fatigue; decompression sickness. This paper outlines the architecture of the CSRM and presents preliminary development milestones completed to-date including preliminary output results of the human thermal regulation model and HNW model to analog suit training events.

II. The Crew State and Risk Model Overview

CSRM aims to provide individualized astronaut-specific physiology and performance models to aid in predicting pre-EVA physiology state and readiness while providing real-time predictive capability during EVA operations. Holistically, it is thought that human state during EVA can be categorized into seven key physiology and performance domains. In EVA spacesuits, there is a reduced pressure and increased oxygen environment, increasing the risk of decompression sickness (DCS).[7,8] The suit is also an enclosed system which requires any heat generated to be removed from the system. In-flight, the main pathways to offload heat physiologically is through convection and conduction with the environment.[9,10] This shifts the thermal regulatory process which the in-suit liquid cooling and ventilation garment (LCVG) helps mitigate.[11] The Human Thermal Regulation model aims to predict suited thermal performance by providing core temperature and heat storage metrics. Weight and mobility are factors that are dependent on the suit pressure and construction and can change with reduced gravity leading to both physical and cognitive fatigue states.[12–15] The CSRM fatigue model enables prediction of physical and cognitive states during an EVA. Mobility and weight of the suit will also generate a performance cost to traversing long distances during EVA.[16–18] The traverse model predicts this performance cost for an EVA planetary traverse. Additionally, since the suit is an enclosed system

there is limited space for a hydration and food system within the suit. Traditionally, crewmembers have 1L of water in the disposable in-suit drink bag (DIDB) for the duration of an EVA (6 to 7 hours long).[19] Currently, there is no food available during the duration of EVA on the ISS.[20] Hydration, nutrition, and waste management (HNW) are factors that will affect EVA success as well as crewmember health and performance. The HNW model aims to estimate hydration and nutrition states for a given planned EVA. Lastly, as the suit is an enclosed system adequate removal of carbon dioxide (CO_2) is required. Increased elevation of CO_2 can cause cognitive and physical affects that can detrimental to the crewmember at high levels.[21] The $PiCO_2$ model predicts suited CO_2 levels, mapped to potential performance implications to aid in decision support. Finally, to analyze specific tasks and directly tie to consumable usage of the suit the metabolic energy expenditure model enables this task tracking and prediction.[14,22]

Historically, the use of metabolic energy expenditure has been used as the primary measure for flight operations to assess consumable usage and crew performance states.[23] Metabolic energy can be used to track oxygen consumption rates and gauge thermal offloading needs, helping to characterize consumables needs and availability of life support systems. Systems and derived calculations were developed to track these needs during EVA operations shortly after early Gemini missions[24]. Currently, metabolic rates continue to be used as the main source reference for crew performance and consumable usage during ISS EVA operations. During real-time operations, metabolic rate telemetry from the suit is calculated using a pressure drop in oxygen associated with oxygen consumption and resultant estimations, such as respiratory exchange ratios. These calculations enable flight operations personnel to make decisions on consumable rates and the need to possibly re-assess the EVA tasks remaining. During EVA planning, crewmember metabolic rates are tied to task loading from ground-based EVA training events to aid EVA planners in assessing tasks based on metabolic loading estimates enabling a more accurate window of consumable usage.[22] NASA

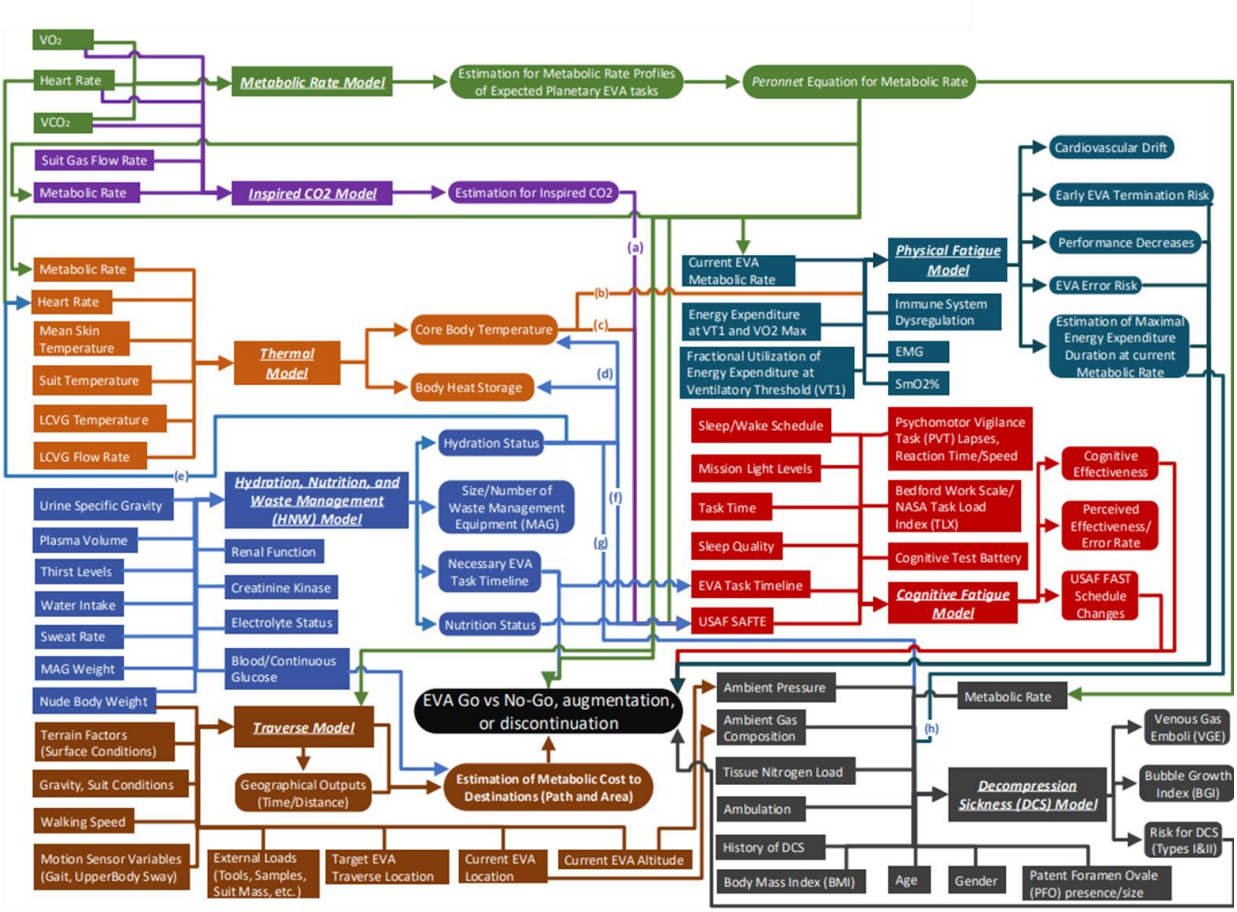


Figure 2. ***The Crew State and Risk Model physiologic map:*** *The CSRM model is comprised of seven core domains that model the crew physiology and performance states pre- and during EVA operations. The above map breaks each model subcomponent interactions wholistically. Each model has input variables that affect not only the independent model for which they are a core input, but also other models where peripheral interactions may exist.*

standards, such as NASA-STD-3001, detail limits to conducting EVA.[25] To improve biomedical informatics capability for lunar and Mars surface EVAs, the CSRM data repository seeks to add components to enable accurate tracking of biomedical flight rules and human performance measures to optimize EVA performance as well as crew health and safety (e.g., core body temperature, hydration status, physical fatigue states).

The development approach and pipeline to enable successful biomedical EVA modeling capabilities rely heavily on expanding the current training pipeline by providing crew performance measures tied to suit operational consumables and flight limits. Additionally, curating an EVA biomedical data repository from crew training events can help expand this training capability. As part of the CSRM suite, data is currently compiled from analog training events from the Neutral Buoyancy Laboratory (NBL), Active Response Gravity Offload System (ARGOS), and a variety of field testing events to curate an "EVA Trials Database." This database drives the ability to customize and personalize CSRM models to crew specific needs and allows input into decision support systems like PersEIDS. The predictive model is a mixture of empirical observations from analog training events and numerical analysis for components related to traverse paths. Each model is described in the below section and has been developed in an initial configuration. Each initial configuration was completed independent from peripheral model correlations or interactions. Synergistically, each model will output a set of physiologic predictions that are expected to influence other CSRM models (Figure 2).[26]

A. CSRM Model Descriptions

This section will briefly describe each model to lay out a framework of each physiology domain and relationship between inputs and outputs. The first model, metabolic energy expenditure, has historically been used in EVA as suit telemetry to determine the work rate of the crew member and associated thermal loading. This CSRM model component provides an estimation for metabolic rate profiles of expected planetary EVA tasks, based on analysis of existing individualized suited training data sets. The baselined model was built using the same framework as ISS EVA operational tasks and will be expanded to include exploration operational tasks as they are developed through EVA simulation development and Artemis/Martian EVA con-ops.[22] A peripheral element of the metabolic model utilizes real-time heart rate to predict metabolic energy expenditure through pre-established linear regressions. Correlated to the metabolic rate model, the inspired CO_2 model provides an estimation for inspired CO_2 using relationships with metabolic rate from suited CO_2 washout studies. An equation has been implemented currently relating a simple average of minimum and maximum regressions, though this data does not currently encapsulate washout performance of exploration spacesuits. Future development will focus on ventilation flow paths and data from CO_2 washout studies to establish a suit-specific model.

The human thermal regulation model estimates core body temperature and heat storage values over the course of an EVA. The model currently uses two prediction methods 1) simple regressions to calculate core body temperature and heat storage levels, 2) Kalman-filter using heart rate to predict core temperature[27]. The main inputs of the human thermal regulation model attempts to utilize biomedical suit telemetry that is already available in-flight to minimize the computational power needed for simple predictions. Additionally, the main heat offloading of the suit is the interaction with the liquid cooling and ventilation garment (LCVG) and the crewmember. Predicting a core body temperature and heat storage will give basic thermal information to make decisions against NASA physiology standards for EVA.[25] Core body temperature also gives a window into performance states that can interact with other models, such as, hydration and fatigue states.

Tied to the thermal model, adequate hydration is critical for metabolism, circulation, regulating temperature. Hydration status can effect exercise performance and recovery,[28,29] The main objective of the HNW model is to provide determination of hydration status during EVA. This model is being updated to also provide a nutrition level to build inputs into other models (e.g., fatigue). As of now there is no nutritional resource within a spacesuit, but future suits will be required to have an ability to have one. The food system for a vehicle currently will require considerations of pre-EVA nutritional needs similar to a high-performance athlete preparing for competition. To track consumables as well nutritional components for EVA are necessary in understanding leading to EVA operational items.[20] The waste-management component will also define the necessary EVA task timeline (e.g., how hydration/nutrition input changes output due to higher intensity EVAs), size of waste management equipment [e.g., Maximum Absorption Garment (MAG))], number of waste management consumables needed for the EVA cadence (i.e., number of MAGs).

The CSRM traverse model estimates the physiologic cost of ambulation in a pressurized space suit from a predetermined landing site or habitat out to a designated exploration point. The model will output metabolic energy expenditure associated with the planned path and provide an optimized path for crew to take saving consumable time. The model at its core relies on map data inputs and breaks the specific map components down into slope and terrain descriptions using digital elevation modeling approaches (DEM). Our metabolic cost function approach applies a



Figure 3. *Hybrid Spacesuit Simulator (HS3).* *The HS3 is a simulated physical workload approximation tool that allows for modular testing of bioinformatics and instrumentation allowing use of a commercial liquid cooling garment and operationally relevant subsystems.*

modified Santee et al. load carriage model which allows for factors to fine tune inputs that are sensitive to delays in metabolic adaptation.[30] The traverse model also utilizes a Pandolf model field-based application of slopes including up, down and level slopes while expanding upon the anthropometry and topographical model inputs.[30] The pathfinding function utilizes A* (or A-star) or Dijkstra's algorithm to compute an optimized paths between EVA locations.[31]

The fatigue model is divided into two sub-domains to capture both physical and cognitive burdens of conducting an EVA. Both submodules will estimate the level of fatigue over the course of EVA. Physical fatigue is predicted by a time to an exhaustion state for a given task using inputs of maximal energy expenditure at aerobic capacity and calculated fractional utilization of energy expenditure at ventilatory threshold 1 (VT1). Cognitive fatigue provides an estimation of EVA task performance via cognitive effectiveness, level of vigilance, and sleep/circadian rhythm.

Finally, the DCS model provides a prediction of risk and sensitivity to DCS that will be present pre-EVA, during EVA, and post-EVA using a common pressure profile input format. The DCS model also calculates decompression stress over the course of a defined pressure or atmosphere profile with associated physical workloads. The initial outputs of this model include Venous Gas Emboli (VGE), risk of DCS Type I and Type II, and bubble growth index (BGI).

III. Initial Development of Thermal and Hydration Models

To develop the initial baseline configuration of the human thermal regulation and HNW models, testing was completed using an analog space suit. Model development used data collected through a CSRM thermal and HNW baseline study (n=6, equal male and female). The dataset included a five hour simulated exploration EVA using the Hybrid Space Suit Simulator (HS3) (Figure 3).[32].

During this study subjects completed an end-to-end EVA timeline in a mission-like fashion starting with a 1500m traverse on a passive treadmill at varying resistances to simulate walking out to a predetermined geology site. Following the 1500m traverse, subjects transitioned from a passive treadmill into a geology analog sandbox to perform a geology task circuit. Continually, subjects performed traverses at varying resistances separated by geology, object relocation, and EVA task board operations to simulate a traverse back to a habitat. The EVA timeline of tasks conducted can be found in Table 1. Following the end-to-end EVA, subjects were allowed a short break and pause in data collection. Then subjects performed standalone tasks, with rest breaks between each task to return to baseline, to

gather steady state data for each independent task found in Table 1. Pre-suit donning nude weight, urine specific gravity, drinking water weight, and food consumption weights were recorded.

Subjects were given 32 ounces of water to simulate the in-suit disposable drink bag (DIDB) throughout the duration of the test. Metabolic rate (COSMED K5, Rome, Italy), heart rate (Polar H10, Polar Electro, Kempele, Finland), core body temperature (eCelsius Performance, BodyCap Inc., Hérouville Saint-Clair, France), skin temperature (iButton hydrochron, Whitewater, WI USA), and liquid cooling garment (LCG) temperatures were collected continuously throughout the test. Post-suit doffing nude weight, urine specific gravity, drinking water weight were collected as repeat measures.

To develop and test the hydration model, data was collected as part of a study conducted at the NBL (n=15) during crew ISS EVA training events. Subjects were asked to complete their nominal pre-training operational routines. Pre-suit donning nude weight, urine specific gravity, drinking water weight, and food consumption weight was collected. Subjects performed a 6 to 7 hour simulated microgravity EVA. Following the EVA, repeat measures were collected post-suit doffing including nude weight, urine specific gravity, and drinking water weight consumed. To test the thermal model outputs, a data set was used that was generated as part of a Lunar Metabolic Rate Characterization Study in the Mark III prototype space suit at Lunar gravity offloading completing the same tasks as Table 1.[14]

Table 1. EVA Task Timeline

EV1 Timeline Tasks	Estimated Task Time
Suit Donning	0:25
Baseline Data Collection	0:05
EVA Circuit: Treadmill walk 1/4: 1500m Traverse (Res 3/4)	0:30
EVA Circuit: Geology Site 1/3; Slope 0; Tool Pair 1	0:05
EVA Circuit: Geology Site 1/3; Slope 0; Tool Pair 2	0:05
EVA Circuit: Geology Site 1/3; Slope 0; Tool Pair 3	0:05
EVA Circuit: Treadmill walk 2/4: 500m (7/8)	0:15
EVA Circuit: Geology Site 2/3; Slope 10; Tool Pair 1	0:05
EVA Circuit: Geology Site 2/3; Slope 10; Tool Pair 2	0:05
EVA Circuit: Geology Site 2/3; Slope 10; Tool Pair 3	0:05
EVA Circuit: Treadmill walk 3/4: 500m (Res 5/6)	0:10
EVA Circuit: Object Relocation; 10 lbs small	0:03
EVA Circuit: Object Relocation; 10 lbs large	0:03
EVA Circuit: Object Relocation; Rest	0:03
EVA Circuit: Object Relocation; 20 lbs small	0:03
EVA Circuit: Object Relocation; 20 lbs large	0:03
EVA Circuit: Treadmill walk 4/4: 500m (Res 3/4)	0:10
Task Board Operations	0:15
Break	0:30
Standalone Circuit: Treadmill Walkback: 2000m (Res 3/4)	0:45
Standalone Circuit: Subjective & Cognitive Ratings	0:10
Standalone Circuit: Geology Drive Tube	0:05
Standalone Circuit: Geology Rake	0:05
Standalone Circuit: Geology Standing Trench	0:05
Standalone Circuit: Geology Float Sample	0:05
Standalone Circuit: Geology Kneeling Scoop	0:05
Standalone Circuit: Geology Sample Tagging	0:05
Standalone Circuit: Subjective & Cognitive Ratings	0:05
Suit doffing	0:25

B. Human Thermal Model Relationships

The human thermal model is an empirical model that draws on observations to predict core body temperature and heat storage from relationships between mean skin temperature, metabolic rate, and heart rate from EVA telemetry. This simple approach allows for customizable and simple calculations using minimal telemetry data for EVA operations. The core temperature predictive relation requires inputs of subject heart rate and metabolic rate and is predicted using a multiple linear regression. Heart rate and metabolic rate values were chosen due to the current usage in flight operations as space suit telemetry to the ground. In the initial development of this preliminary baseline model using n=6, data was compiled into a dataset for metabolic rate and heart rate. A multiple regression was then calculated to relate those inputs to core body temperature allowing a general predictive equation. Similarly, a multiple regression was calculated for the mean skin temperature from inputs of metabolic rate and delta LCG temperatures. The delta liquid cooling garment temperature is the absolute difference between inlet and outlet temperatures of the LCG. The represented multiple regressions for core body temperature and mean skin temperature are represented in equations 1 and 2.

$$CT = b_0 + b_1 HR + b_2 MR \tag{1}$$

$$SKT = c_0 + c_1 MR + c_2 DLCG \tag{2}$$

Where CT is core body temperature, HR is heart rate, and MR is metabolic rate. The multiple regression coefficients are represented for CT as the intercept b_0, HR coefficient b_1, and MR coefficient b_2. SKT is mean skin temperature and DLCG is the delta LCG temperature. The multiple regression coefficients are also represented for SKT as the intercept c_0, MR coefficient c_1, and the DLCG coefficient c_2. Prior to calculating the regression coefficients for CT, a min-max scalar normalization was applied to the dataset of MR and HR to calculate CT using equations 3 and 4.

$$X_{Norm,\ MR} = \frac{X_{MR} - X_{\min,\ MR}}{X_{max,\ MR} - X_{min,\ MR}} \tag{3}$$

$$X_{Norm,\ HR} = \frac{X_{HR} - X_{\min,\ HR}}{X_{max,\ HR} - X_{min,\ HR}} \tag{4}$$

Where X_norm is the scalar applied to MR and HR prior to the regression calculations, X is the MR or HR value respectively, X_{min} is minimum MR or HR within the independent dataset, and X_{max} is the maximum MR or HR within the independent dataset. Using both predicted CT and SKT, heat storage (Q) is than calculated using equation 5 [33]. Where m_{body}, is the mass of the individual, $c_{p,body}$, is the specific heat of the body, ΔSKT is the predicted mean skin temperature difference, and ΔCT is the predicted core temperature difference and converted to BTU/hr as the final unit.

$$Qstor = m_{body} c_{p,body} (0.2\Delta SKT + 0.8\Delta CT)/1.055 \tag{5}$$

C. Hydration State Model

The hydration state model is the first empirical model for the HNW element of CSRM and is developed in its current state to predict the change to hydration state between pre- and post-EVA using inputs of nude body weight, drinking water weight, urine void weight, food intake, and urine specific gravity. The difference between the pre- to post-hydration state results in the wholistic hydration state effected by the performed EVA. Hydration state pre-EVA is compiled as the day of pre-EVA state H_n, and H_{n+1} as the post-EVA state both described in equations 6 and 7.

$$H_n = [(1.3BW_{PRE} + 1.411DIDB_{PRE} + 1.42MAG_{PRE} - 1.0FOOD_{PRE})0.64] +/- 1.35USG_{PRE} \tag{6}$$

$$H_{n+1} = [(1.3BW_{POST} + 1.411DIDB_{POST} + 1.42MAG_{POST} - 1.0FOOD_{POST}) * 0.64] +/- 1.35 * USG_{POST} \tag{7}$$

Where BW is body weight, DIDB is the disposable in-suit drink bag and water weight, Maximal Absorption Garment (MAG) is the void weight, FOOD is the food intake weight, and USG is the urine specific gravity. The USG is added or subtracted based on hydration trend. FOOD was subtracted out of the hydration state equation to

remove the offset due to eating prior to the EVA event. The final hydration state H_{state} is then defined by the percent difference of H_n and H_{n+1} as defined in equation 8.

$$H_{state} = \frac{(H_n - H_{n+1})}{H_n} * 100 \quad (8)$$

The hydration trend was empirically derived with associated zones defined by the three variables that have the highest impact on hydration.[29] These variables are body weight changes, hydration water intake as measured by changes in DIDB weight, and urine specific gravity (USG). The delta of each variable between pre- and post-EVA provided the shift in that variable depending on hydration. There is mixed literature on agreement for each variable. For example, in sports medicine, BW is the highest contributing factor, whereas USG can be defined as an absolute hydration state. Once the delta values were calculated between pre- and post-EVA, the average score of these three values then determined the neutral, positive, or negative hydration trend. This hydration trend was then compared to the final H_{state} between H_n and H_{n+1} to determine accuracy of the correct categorization of hydration state.

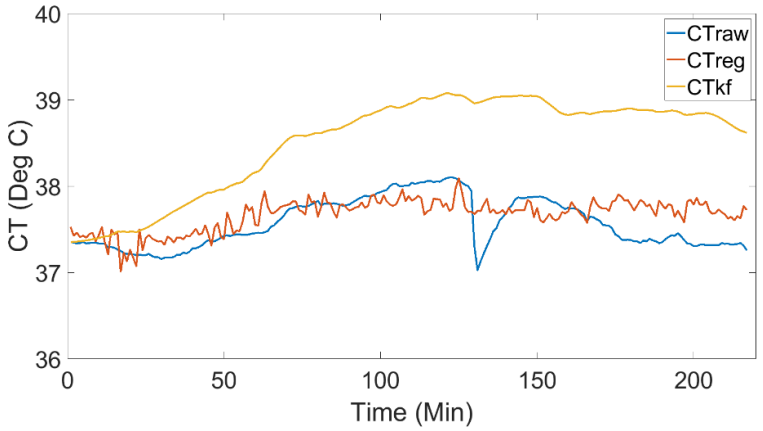


Figure 5. Core body temperature prediction during simulated lunar EVA in Mark-III pressure suit. *The plot represents a comparison of the CSRM human thermal model CT prediction and a field based Kalman filter approach to CT raw data collected during lunar simulated EVA at ARGOS in the Mark-III pressure suit. CT_{reg} represents the output of the CSRM regression model, CT_{kf} represents outputs of the Kalman filter, and CT_{raw} represents the subject raw data. The CSRM CT_{reg} captures the general average response of the core body temperature across the simulated EVA in comparison to the field based CT_{kf} values which slightly over predict. This over prediction is due to the usage of a full body liquid cooling garment which the CSRM model considers in its empirical data approach.*

IV. Preliminary Results

Model development for the human thermal regulation predictions focused on the relationships of heart rate, metabolic rate and the target predicted output of core body temperature. The initial spread of data showed agreement of a linear trend from data collected during EVA tasks in the HS3 analog, as seen in Figure 4. Average error for core body temperature (CT) predictions were 0.25 ± 0.19 °C for the baseline HS3 dataset.

Other models to predict core body temperature have been developed utilizing the empirical data observation approach. Bueller et al., utilizes heart rate observations from field based military training operations to develop a Kalman filter technique that estimates core body temperature.[27] The CSRM team tested the core body temperature regression model developed using a liquid cooling garment within the HS3 against a field based Kalman filter approach using ARGOS lunar metabolic rate characterization data. The general regression equation was used and was not individualized based on subject. Outputs from the general regression trended towards the average response of core body temperature from preliminary ARGOS lunar offloading and simulated EVA tests. However, the output predictions did not fluctuate across the maximum and minimum bounds. In comparison, using heart rate from a field based developed model corresponded to overpredictions of core body temperature when in lunar offloading and using a liquid cooling garment (Figure 5). The CSRM core body temperature regression model

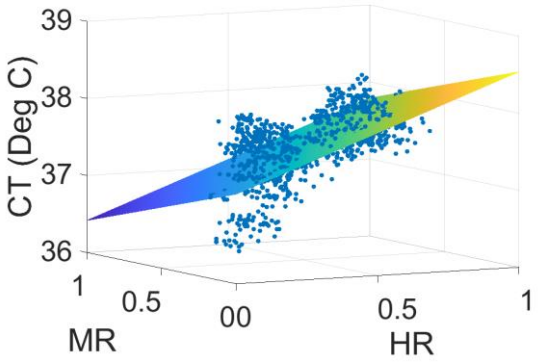


Figure 4. Metabolic Rate, Heart Rate, and Core Body Temperature trend in the Hybrid Spacesuit Simulator. *The spread of data during the preliminary thermal model data collection shows a linear trend relation between MR, HR and the target output CT.*

predicted core temperature during ARGOS lunar runs with an error of 0.2 ± 0.15 °C, while the field-based model produced an error of 0.95 ± 0.44°C.

Hydration state outputs of the HNW model had shown initial mixed prediction accuracy that did align to tested designations of hydration trend. The model output of predicted hydration state for the general testing NBL cohort at a 70% accuracy between a pre- and post-EVA. The model trended towards more inaccuracy during phases when subject started the EVA in a more dehydrated state or there was only a minor change between the start and finish of the EVA (Figure 6). This caused the model to underpredict their hydration due to the limited control of pre-hydration data leading up to the EVA event.

	BW delta	DIDB delta	USG trend	Average hydration status	H_n and H_{n+1}	H_{state}
HS3 DATA	-0.726275016	0.786	Improved a lot	Hydrated	65.85 64.53	2.013910
	-0.921776981	0.717	Worsened a lot	Neutral	51.58 50.54	2.014591
	-0.085731782	0.748	Worsened, but little change	Marginally hydrated	65.21 63.96	1.905392
	-0.659179687	0.48	Worsened a lot	Neutral	67.40 66.90	0.742076
NBL DATA	-0.386100386	0.834	Worsened but not a lot	Marginally Hydrated	64.22 63.54	1.051083
	0	0.154	Worsened but not a lot	Neutral	71.29 71.15	0.202272
	0.306818182	0.368	Worsened a lot	Neutral	72.87 72.95	-0.106302
	0	0.889	Worsened but not a lot	Marginally Hydrated	49.51 48.96	1.098340
	-0.132275132	0.799	Worsened but not a lot	Marginally Hydrated	62.46 61.79	1.082127
	-0.624638519	0.379	Improved	Marginally Hydrated	74.33 73.54	1.055527
	-0.51477171	0.128	Improved	Neutral	76.65 76.43	0.290501
	0.388042541	0.722	Worsened but not a lot	Marginally Hydrated	57.50 57.08	0.729138
	0.225225225	0.447	Improved	Marginally Hydrated	68.81 68.57	0.357925

Figure 6. Hydration state outputs for HS3 and NBL data showing predictive examples and use cases of the CSRM HNW model. *The data displayed above shows the three main drivers of hydration for EVA which is body weight change pre- to post-EVA (BW delta), water intake during EVA (DIDB delta), and urine specific gravity (USG). In this case USG shows a trend pre- to post- EVA of the subject hydration status. The three variables are then averaged for our empirical approach to observe a scale of hydration status. Using the H_n and H_{n+1} calculations above, we get the final hydration state values as a corresponding difference represented by the H_{state}.*

V. Discussion

Traditionally, human thermal models take a numerical methods approach to setup the environmental conditions, require estimation of the current physiologic state as inputs, estimate expected work rates, and require predefined thermal offloading paths.[34,35] While these numerical methods are essential for pre-mission design for spacecraft and suit functionality, the modeling approach is cumbersome and is not able to support real-time computations. By taking an empirical modeling approach, simple inputs can be used to predict physiologic states of core body temperature which is generally used in physiology literature to define thermal burden.[36] To estimate thermal consumables tied to metabolic consumption, heart rate, metabolic rate, and liquid cooling garment temperatures are the only current pieces of data that are required for CSRM to make adequate predictions of thermal state for decision support needs. Empirical modeling enables fine tuning while allowing for quick individualized data analysis. To generate core body temperature predictions, the CSRM human thermal regulation model uses a simple multiple regression relation to represent core body temperature effectively in a pressurized suited condition, in contrast to other empirical approaches (shown in Figure 5) which utilize a Kalman filter approach based on terrestrial field data to draw correlations between heart rate and core body temperature.[27] One caveat of empirical modeling approaches is the relationships are built on analog

training data or experimental observations. These assumptions during data collections, if not defined correctly, can produce error. The outputs represented in this paper of the CSRM human thermal model are the output of a generalized multiple regression using the data across multiple subjects and testing events. Prediction accuracy can be improved by using an individualized multiple regression developed from subject training data. It is the goal of the CSRM to produce crew-specific models to enable accurate thermal predictions for use in operational training and flight using the same multiple regression approach.

Similarly, the hydration model component of the HNW domain represents pre- and post-EVA crew hydration states taken from empirical operations during EVA training events and testing. Simple inputs of body weight changes, drinking water intake, void amount, and urine specific gravity allows predictions of hydration trends and state due to the EVA training event. During the development of the HNW model, the NBL data that was collected was not controlled based on EVA type and task timeline. This is due to the high-quality observations gathered to determine hydration strategy during preparation of EVA operations. The future model testing and development will control for EVA task and timeline to enable hydration state predictions based on EVA type. One caveat of the current hydration prediction model is it is primarily pre- to post-EVA. The model can be made more accurate by allowing for determinations of real-time EVA hydration states through tracking water intake and sweat rates. When looking at EVA cadence for the Artemis program, crew will be expected to conduct multiple back-to-back EVAs in the relatively short time they will be on the Moon. Having a pre-defined hydration state and subsequent hydration states post-EVA will give the crew the ability to assess their recovery time and individualized strategies prior to the next EVA event. Furthermore, the hydration state model can be made more accurate by applying a normalization technique. The current equations are built on a general empirical observation of a full dataset, but applying a normalization technique and providing individual crew observations would enable more accurate predictions and tuning of individualized hydration strategies. The future model development will include a nutritional component during EVA operations to help in predicting calorie usage and energy demand.

VI. Conclusion

Artemis EVAs will enable further exploration capabilities through sustained presence on the lunar surface. EVAs during on the Moon will be able to draw on the ability to use near real-time communications and decision support from Earth ground operations. Looking forward to Mars, crew will be subjected to increased communications delays that will require them to work more autonomously. This paper presented the development of the Crew State and Risk Model to-date, which provides physiologic state and EVA risk determinations to enable Earth-independent biomedical decision support operations. Preliminary results were presented for the Human Thermal Regulation and Hydration, Nutrition, Waste management models as precursors to The Moon-to-Mars infrastructure will continue to drive development of the CSRM model architecture to aid in EVA planning and science task execution for early Artemis EVAs, while keeping crew members safe by drawing on individualized models and training paradigms.

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References

1. Miller, M. J., Claybrook, A., Greenlund, S., Marquez, J. J. & Feigh, K. M. Operational Assessment of Apollo Lunar Surface Extravehicular Activity. (2017).

2. Broyan, J. L., Abercromby, A. F. & Appelbaum, M. L. Crew Health and Performance (CHP) Technology Roadmaps.

3. Abercromby, A. *et al.* NASA's top human system research and technology needs for Mars. *Acta Astronaut.* **228**, 931–939 (2025).
4. Stevens, A. H. *et al.* Tactical Scientific Decision-Making during Crewed Astrobiology Mars Missions. *Astrobiology* **19**, 369–386 (2019).
5. McGrath, T. *et al.* A Decision Support System for Extravehicular Operations Under Significant Communication Latency. in (Calgary, Alberta).
6. Abercromby, A. *et al.* NASA Crew Health & Performance Capability Development for Exploration: 2022 to 2023 Overview. (2023).
7. Abercromby, A. F. J. *et al.* Crew Health and Performance Extravehicular Activity Roadmap: 2020. (2020).
8. Abercromby, A. F. J., Garbino, A., Makowski, M., Norcross, J. & Sanders, R. Updates to NASA's Break-in-Prebreathe Rules Due to Type II Decompression Sickness Risk Considerations. (2024).
9. Stahn, A. C. *et al.* Increased core body temperature in astronauts during long-duration space missions. *Sci. Rep.* **7**, 16180 (2017).
10. Hoffmann, B. Evaluation Of Heart Rate Variability And Cardiovascular Regulation To In-Flight Workload And Thermal Stress.
11. Hoffmann, B. *et al.* Human Thermal Analysis of Traverse and Geology Tasks During Simulated Lunar Extravehicular Activity. in *2023 IEEE Aerospace Conference* 1–8 (2023). doi:10.1109/AERO55745.2023.10116010.
12. Strock, N. *et al.* EVALUATION OF AEROBIC CAPACITY IN RELATION TO SIMULATED LUNAR SURFACE EXTRAVEHICULAR ACTIVITIES. | EBSCOhost. vol. 95 454 https://openurl.ebsco.com/contentitem/gcd:178876150?sid=ebsco:plink:crawler&id=ebsco:gcd:178876150 (2024).
13. Strock, N. C. *et al.* Evaluation of Aerobic Standards for Lunar Surface Extravehicular Activities. in (Galveston, TX).
14. Schlotman, T. E. *et al.* A Preliminary Assessment of Physical Demand During Simulated Lunar Surface Extravehicular Activities. in (Big Sky, MT).
15. Schlotman, T. E. *et al.* A Preliminary Assessment of Cognition and Fatigue During Simulated Lunar Surface Extravehicular Activities. in (New Orleans, LA).
16. Kim, K. J., Hoffmann, B., Estep, P., Marshall-Goebel, K. & Buckland, D. Improving Metabolic Workload Estimation Accuracy for Planning and Analyzing Exploration Traverses.
17. Kim, K. J. *et al.* Uneven terrain affects metabolic cost and gait in simulated complex lunar surfaces. *Physiol. Meas.* **44**, 104001 (2023).
18. Teunissen, L. P. J., Grabowski, A. & Kram, R. Effects of independently altering body weight and body mass on the metabolic cost of running. *J. Exp. Biol.* **210**, 4418–4427 (2007).

19. Downs, M. & Norcross, J. Crew Performance and EVA Requirements. in *Handbook of Lunar Base Design and Development* (eds. Eckart, P. & Aldrin, A.) 1–24 (Springer International Publishing, Cham, 2020). doi:10.1007/978-3-030-05323-9_3-1.
20. Dillon, E. L. *et al.* Recommendations for developing space suit integrated food systems and delivering nutrition before, during, and after lunar EVA.
21. Mitchell, K. & Norcross, J. CO2 Washout Testing of the REI and EM-ACES Space Suits. in *42nd International Conference on Environmental Systems* (American Institute of Aeronautics and Astronautics, San Diego, California, 2012). doi:10.2514/6.2012-3549.
22. Cox, L. *et al.* EVA Planning: Using Neutral Buoyancy Laboratory (NBL) Training to Predict in-Flight Energy Expenditure.
23. Paul, H. Energy Expenditure During Extravehicular Activity Through Apollo. in *42nd International Conference on Environmental Systems* (American Institute of Aeronautics and Astronautics, San Diego, California, 2012). doi:10.2514/6.2012-3504.
24. Carpentier, W. R., Coons, D. O. & Kelly, G. F. Medical aspects of Gemini extravehicular activities. (1968).
25. Whitmore, M., Boyer, J. & Holubec, K. NASA-STD-3001, Space Flight Human-System Standard and the Human Integration Design Handbook. in (Orlando, FL, 2012).
26. Roche, D., Buckland, D. & Hoffmann, B. Crew State and Risk Model (CSRM) - An Integrated Physiologic Map for Exploration Class EVA Predictive Modeling and Operations.
27. Buller, M. J. *et al.* Estimation of human core temperature from sequential heart rate observations. *Physiol. Meas.* **34**, 781 (2013).
28. Lee, E. C. *et al.* Biomarkers in Sports and Exercise: Tracking Health, Performance, and Recovery in Athletes. *J. Strength Cond. Res.* **31**, 2920 (2017).
29. Barley, O. R., Chapman, D. W. & Abbiss, C. R. Reviewing the current methods of assessing hydration in athletes. *J. Int. Soc. Sports Nutr.* **17**, 52 (2020).
30. Santee, W. R., Blanchard, L. A., Speckman, K. L., Gonzalez, J. A. & Wallace, R. F. Load Carriage Model Development and Testing with Field Data. *US Army Res. Inst. Environ. Med. TN03-3* (2003).
31. Johnson, A., Hoffman, J., Newman, D., Mazarico, E. & Zuber, M. An integrated traverse planner and analysis tool for planetary exploration. *AIAA Space 2010 Conf. Expo.* (2010).
32. Hew, M., Hoffmann, B., Wusk, Z. & Somers, J. Developing a Hybrid Space Suit Simulator as a Research Tool for Assessing Extravehicular Activity Relevant Workload. in (Calgary, 2023).
33. Rhodes, R., Bue, G., Meginnis, I., Hakam, M. & Radford, T. Thermal Performance Testing of EMU and CSAFE Liquid Cooling Gannents. in (Reston, VA, United States, 2013).

34. Weber, J. Revision and Optimization of the Wissler Thermal Model – Assessment, Analyzation, and Rework of the Passive Model. (2018).
35. Song, H. J. Overview of Human Thermal Modeling, Thermoregulation, and Thermal Comfort at NASA. (2017).
36. Laxminarayan, S., Buller, M. J., Tharion, W. J. & Reifman, J. Human Core Temperature Prediction for Heat-Injury Prevention. *IEEE J. Biomed. Health Inform.* **19**, 883–891 (2015).