DEEP SPACE SPACEFLIGHT: THE CHALLENGE OF CREW PERFORMANCE IN AUTONOMOUS OPERATIONS. S.S. Thaxton [1], T. J. Williams[1], P. Norsk[3], S. Zwart[3], B. Crucian[1], E. Antonsen[1]. [1]NASA Johnson Space Center (2101 NASA Pkwy, Houston, TX, Sherry.S.Thaxton@nasa.gov, brian.crucian-1@nasa.gov, erik.l.antonsen@nasa.gov, thomas.j.williams-1@nasa.gov), [2]Behavioral Health & Performance Laboratory, KBRwyle/NASA Johnson Space Center, Houston, TX, USA, pete.roma@nasa.gov, [3]TMB (301 University Blvd, Galveston, TX 77555, sara.zwart-1@nasa.gov).

Introduction:

Distance from Earth and limited communicatons associated with Long Duration Exploration Missions (LDEMs) will increase the demands for crew autonomy and dependence on automation (i.e., completing tasks using onboard systems, without close supervision or coordination with Mission Control Center (MCC)) [18, 19, 3], and Deep Space Gateway presents a unique opportunity to study the impacts of these increased demands on human performance. The importance of understanding how Deep Space Gateway and Transport (DSG/T) missions may alter both operations and safety is revealed by previous missions (e.g., Mir, Skylab) which manifested on an Apollo mission as tension between the crew and the MCC [11]. Results from a recent ISS study [16] demonstrated that instituting just a 50-second communication delay with MCC were associated with reduced ratings of crew well-being and communication quality on communication-delayed tasks, when compared to real-time communication tasks. Communication delays were also associated with increased stress and frustration, and qualitative data suggested communication delays negatively affected task efficiency and teamwork processes. In two NASA analog studies (HERA and NEEMO) with comm delays of 5 to 10-minutes, crews committed more errors and required time-consuming assistance, with both crew and analog control centers reporting decreased effectiveness each way as compared to non-comm delay days [8]. With more autonomous operations, there is a need to better understand human–machine interactions and the human-interface related to LDEM requirements (cf., the collision of Progress 234 with the Mir space station) [3, 7]. We must anticipate that LDEM missions will consist of dynamically changing functions, at times being executed concurrently and sequentially—demanding different allocation schemes between human, computer, or MCC resources[14]. Increased exposures to known spaceflight hazards increase the importance of better characterizing the cognitive, motivational, and affective components of both crew/team performance and the human–machine system framework [13]. Human processes are defined as actions that convert inputs to outcomes through cognitive or behavioral activities [9]. LDEM spaceflight will involve multiple task variables that will involve dynamic allocations of control between crew, onboard systems, and mission control to increase overall system performance [10]. Human processes and states not only influence the outcomes of safety and performance but also can be affected by other preexisting factors. Thus, measurement of these variables is highly informative and necessary to achieve successful human–machine interaction. The DSG missions offer an important opportunity to better undersand the interplay of training, skills, completing tasks with and without automation support in preparation for future DST missions that necessitate a more autonomous environment. We also must understand the impact of different adaptive/responsive systems that allow an interdependent autonomy (i.e., between crew and onboard systems) in order to assess the effect on crew mental health, performance and team processes as these missions become more autonomous [7, 1].

Methods:

We propose assessing the variables that affect the human-machine systems: the multitasking environment, task type, task load, and task complexity requirements for crew that can impact on performance [6]. We propose to leverage the visual attention components of a cognition battery [2] along with assessments of key factors that influence human performance, e.g., visual attention, mental workload, situational awareness [9] trade-off between performance, workload, and situation awareness with the inclusion of degrees of automation [15]. We also propose to assess crew interpersonal traits and individual differences given how these attributes influence and affect both coping with workload demands (and therefore allocation of tasks) and performance [20]. We propose to assess the dynamic allocation of adaptive and responsive systems in response to crew vs mission control vs onboard systems in order to assess the overall system performance in human vs automation adaptability in support of autonomous systems [5]. We propose to assess the multitasking environmental demands to assess LDEM mission requirements during which crew is required to switch between tasks to assess effectiveness of multitasking, while assessing perceived reliability of automation and how that varies based on crew's workload [6]. We propose to assess task load (i.e., number of resources or demands crewmember is responsible for) and how that relates to both workload and situational awareness [4,17]. We will also assess crew ratings of task com-

plexity using the following characteristics: (a) the number of elements included in the task, (b) relationship between task elements, and (c) how this relationship evolves with both skill and adaptive allocations to determine how the intrinsic characteristics that influence task performance [12, p. 559]. These assessments will assist NASA in predicting and quantifying the complex interplay of allocation of tasks and performance demand allocations between automotion and robotic systems and their interface and influence with human performance and spaceflight system safety to inform and evaluate system design features in the context of longer-duration missions.

Collection of longitudinal physiological and behavioral metrics (such as cognition, fine motor skills, task monitoring and others) and monitoring in-mission clinical events will enable an assessment of whether in-flight changes in the proposed biomarkers can be used as early predictive measures of human performance changes over the duration of the mission.

Resources Required: Pre-, in-, and post-mission assessments task performance skill capability, situational awareness, cognition battery testing, and measures of trust in automotion, along with assessments of attitudes toward autonomous missions are needed. Pre-mission assessments of interpersonal traits is also needed. We propose to leverage Cognition Battery testing and biomarkers that are part of HRP Standard Measures.

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