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Validation of Self-Scheduling Countermeasures in NASA's HERA Campaign 6

John A. Karasinski*
NASA Ames Research Center, Moffett Field, CA 94043, USA

Shivang Shelat†
San José State University, Moffett Field, CA 94043, USA

Jessica J. Marquez‡
NASA Ames Research Center, Moffett Field, CA 94043, USA

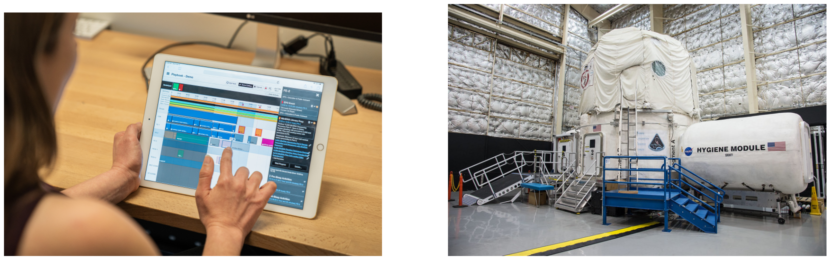
Enhancing crew capabilities for planning and scheduling activities is critical for periods of increased crew autonomy in future long-duration missions where communication delays preclude real-time ground support from Earth. Our study focuses on how to empower astronauts to manage their timelines independently from the experts in the mission control center (MCC). Our objective was to evaluate the impact of scheduling countermeasures on crew scheduling performance, workload, and usability in an analog mission environment. The study involved 16 crew members across four missions in the Limited Autonomy phase of Human Exploration Research Analog (HERA) Campaign 6. Crew members used Playbook to schedule one operational day for the entire crew. Half the participants accessed scheduling aids, and we compared their performance to a control group with no aids. Performance, workload, and usability were assessed using time on task, violation counts, NASA Task Load Index (NASA-TLX), and System Usability Scale (SUS). Participants using scheduling aids completed sessions 20% faster and committed 33% fewer violations. While these differences were not statistically significant due to the study's operational limitations, trends indicate that scheduling aids may reduce errors and improve efficiency. These results can inform the design of scheduling tools to enhance astronauts' autonomy in long-duration space missions, contributing to improved crew performance and reduced reliance on ground support.

I. Introduction

The success of future long-duration human spaceflight depends on the autonomy of onboard crew members, especially in environments where communication delays and operational complexities hinder real-time intervention from Earth-based mission control center (MCC) personnel. Addressing this challenge calls for enhancing astronauts' capabilities to plan, adapt, and execute mission activities autonomously. Researchers have advocated for a new operations paradigm tailored for missions beyond low Earth orbit [1, 2]. The inherent communication delays and increased mission complexity associated with Martian or lunar expeditions necessitate a decentralization of mission planning, shifting the locus of control from Earth to onboard systems and crew. This paradigm requires the development of planning and scheduling frameworks that integrate contributions from ground-based and onboard personnel, enabling astronauts to autonomously manage real-time operations and modify mission timelines in response to evolving conditions.

NASA is researching methods to improve astronaut capabilities for future long-duration space missions, where crew members are expected to operate with greater independence from MCC. Our research focuses on enabling autonomy by operationalizing self-scheduling, where astronauts are empowered to manage their own timelines; this contrasts with the current standard, where a team of experts on the ground controls scheduling [3]. Astronauts, in contrast to ground control planners, are not necessarily experts in scheduling complex timelines with many constraints and requirements. There is a risk of inadvertently increasing astronauts' daily workload by asking them to self-schedule. Thus, we aim to minimize the burden by providing countermeasure aids that may facilitate self-scheduling. By assessing

*Human Factors Researcher, Human-Computer Interaction Group, AIAA Member.
†Student Researcher, Human-Computer Interaction Group
‡Human Factors Researcher, Human-Computer Interaction Group, AIAA Member



(a) (b)

Fig. 1 (a) A participant demonstrates using Playbook on an iPad. (b) The NASA HERA Analog Habitat, pictured at NASA Johnson Space Center.

the effectiveness of scheduling aids, we aim to understand their impact on crew scheduling in an operational context, enhancing our approach to supporting autonomy during long-duration missions.

Playbook is an interactive, web-based platform designed to facilitate crew members' visualization of their schedules and constraints, enabling effective collaboration among themselves and remote MCC personnel (see Fig. 1a). Playbook is an operational timeline tool deployed during the Human Exploration Research Analog (HERA) campaigns at NASA's Johnson Space Center (see Fig. 1b) [3]. Using Playbook, astronauts can schedule and manage their activities directly, accommodating individual preferences and constraints. HERA Campaign 6 (C6), conducted from September 2021 to March 2023, consisted of four missions (M1–M4) and marked the first implementation of self-scheduling within an analog mission setting [4]. We used this opportunity to assess the impact of new scheduling aids (i.e., no-go zones and potential fixes) in the Playbook user interface on crew performance and workload in a simulated operational environment. These new aids were created to help the crew schedule their operational timelines more efficiently while minimizing constraint violations within the plan. This paper presents the findings from our HERA experiment, in which we validated the efficacy of our scheduling aids.

II. Background

A. Planning and Scheduling in Spaceflight

Recent literature on planning and scheduling for spaceflight missions has broadly focused on increasing operational efficiency through optimizing resource allocation or enhancing mission resilience. Human involvement in planning and scheduling spaceflight timelines ranges from automated scheduling tools that do not rely on ground-based control to human-centered approaches that empower astronauts to manage their schedules autonomously from MCC.

As most spaceflight missions do not involve human crew, planning and scheduling literature primarily focuses on automated planning and multi-objective optimization to improve mission resilience. The Simple Planner [5], MEXEC [6], and APGEN [7] were created so that spacecraft could perform their tasks more autonomously without relying on ground control to make every decision. Optimization techniques like Aurora [8, 9], gene-splicing-based search [10], and Ant Colony System (ACS) [11], among others, can reduce overall timeline durations and improve resource utilization. Scheduling techniques such as Hierarchical Task Network-Timeline (HTN-T) scheduling methods [12] and semi-Markov decision processes (SMDPs) [13] offer other approaches to addressing the complexity of task dependencies and resource allocation. Simulation-driven planning tools like SSim [14] have been used to predict scheduling problems ahead of execution and can create more robust plans.

Research has also been aimed at developing integrated mission planning and operational modeling for ground operations for spaceflight missions. Barreiro et al. proposed a peer-to-peer planning architecture for International Space Station operations, which integrates diverse MCC disciplines (e.g., crew activity planning and power management) to allow automated solutions to adapt to changing conditions in real time and to reduce the need for continuous human intervention [15]. This approach enhances coordination between distinct mission planning domains while ensuring flexible responses to unexpected events. Research into Orion Multi-Purpose Crew Vehicle ground operations aimed to streamline pre-launch and post-landing activities [16]. Employing visualization tools, discrete event simulations, and human factors analysis improved the efficiency of ground operations. The OPSMODEL simulation tool produces quantitative assessments of crew tasking effectiveness under various operational scenarios, enabling predictive adjustments and data-driven decision-making and reducing the need for direct ground intervention [17]. While these efforts allow missions to accomplish their scheduling and planning objectives, they do not focus on enabling human-led planning and scheduling.

Mixed-initiative planning systems, in which humans and machines collaborate to develop and manage plans [18], have emerged as a technique to enable crew autonomy. Several researchers have proposed mixed-initiative systems that integrate optimization algorithms with computational models to enable astronauts to make critical decisions on-site, thereby reducing reliance on Earth-based planners [2, 19, 20]. This architecture balances human expertise and automated scheduling capabilities, allowing astronauts to adjust mission timelines in response to unforeseen events and enhancing real-time decision-making processes. Similarly, our previous work operationalized crew self-scheduling as an approach to mission autonomy [3]. Using Playbook, our research investigates how astronauts can independently modify their timelines, incorporate new tasks, and resolve scheduling conflicts. Evaluations conducted during the NASA Extreme Environment Mission Operations (NEEMO) analog demonstrated that these capabilities can be effectively used in complex, spaceflight-like environments, empowering astronauts with greater control over mission planning and execution [3].

B. Self-Scheduling in Other Domains

Although the literature on self-scheduling in the spaceflight domain has gained traction only in recent years, we may draw a parallel between crewed space missions and nursing environments [21]. Both are demanding but offer little opportunity for their constituents, often under high workloads, to contribute their insight to their work schedules. According to the control-demand model [22], high demand and low control may strain job satisfaction and effectiveness. Evidence from healthcare has suggested that nurses who self-schedule report enjoying having control over their workflow [23]. Schedule control has been established as a powerful predictor of job satisfaction, commitment to their organization, burnout, and the intention to leave their hospital [24]. Therefore, a possible solution to avoiding the negative consequences of high demand and low control in space missions is to increase control through self-scheduling, enhancing crew satisfaction.

However, research on the actual self-scheduling process using software tools has received far less focus than the impact of self-scheduling on work-related outcomes. To optimally self-schedule, one must organize their tasks effectively and efficiently, completely understanding all the constraints and availability of limited resources. We argue that developing and validating countermeasures to relieve workload and enhance scheduling can improve crew efficiency and performance. Work beyond the spaceflight domain has aimed at designing scheduling tools that offload workload to an automated system while keeping the human planner in the loop to make important decisions that reflect priority or preferences. For example, Cranshaw et al. created a prototype of an automated scheduling assistant to relieve scheduling-related burdens from users [25]. The user described the constraints of a to-be-scheduled event, and the assistant handled the scheduling. Descriptive usability analyses indicated that users felt the assistant saved time and made them more productive. Making the scheduling workflow easier for users is a worthwhile priority, especially for those who are part of a team and whose schedule adherence is critical for broader performance (e.g., crew success in a deep space exploration mission).

This work discussed evidence for the usability and feasibility of a scheduling tool in the real world. Indeed, when developing and validating tools for high-stakes contexts, it is critical to quantify performance metrics and draw comparisons with countermeasure support versus without (e.g., [26]). Understanding the impact of scheduling countermeasures on specific performance indices then validates those countermeasures for deployment in the real world. A primary aim of the present work is to quantify and compare self-scheduling with and without visual interface countermeasures designed to enhance performance in a spaceflight-like setting.

III. Methods

During each of HERA C6's four missions, four astronaut-like crew members participated in a simulated 45-day mission to the Martian moon Phobos (see Fig. 1b). In this campaign, crew autonomy was defined as the crew's ability to manage their operational timelines independently of MCC. The missions were structured into three distinct phases:

- No Autonomy: The crew could not alter their timelines for the initial seven days.
- Limited Autonomy: During the following eight days, the crews could reschedule most activities in coordination with MCC.
- High Autonomy: In the final thirty days, the crews could self-schedule without coordinating with MCC.

Our study took place within the Limited Autonomy phase, wherein a new operational strategy was employed: each crew member took turns acting as the 'assigned planner' to schedule one operational day for the entire crew. This resulted in a total of 16 self-scheduled days during C6. The assigned planner's responsibilities included leading a Team Preference Meeting (TPM) and conducting a Self-Scheduling Session.

During NEEMO self-scheduling, it was observed that some crew teams had a meeting to discuss their assigned self-scheduling sessions. For HERA's TPM, we directed the assigned planner to facilitate an open discussion to determine the crew's timeline preferences, such as allocating substantial afternoon free time or scheduling morning hygiene periods. This collaborative discussion was designed to ensure that the resulting schedule would reflect the collective preferences of the crew. Following the TPM, the crew planner was tasked with independently constructing the operational timeline during the scheduling session, incorporating the agreed-upon preferences into their operation schedule. We allotted thirty minutes for the TPM and one hour for the scheduling session for each session. An analysis of the conversations during the TPMs is available in Shelat et al. [27]. After the scheduling session, the assigned crew planner assessed their workload using the NASA Task Load Index (NASA-TLX) [28]. Workload is a construct that represents the cost incurred by a human operator to achieve a particular level of performance. To assess a participant's overall workload using the NASA-TLX, the participant evaluates six subjective subscales (i.e., Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration) and then identifies which are more important to their workload through pairwise comparisons. This process creates individual weightings for each subscale, and the frequency with which a participant selects each subscale contributes to its weighted score.

Subsequently, the crew implemented the planned schedule, after which the assigned planner provided insights into their experience through a brief questionnaire [4]. Finally, the planner rated Playbook's usability using the System Usability Scale (SUS) [29]. The SUS is a ten-item Likert scale giving a global view of subjective assessments of usability. A usable system allows users to perform tasks safely, effectively, and efficiently while enjoying the experience. This structured approach to autonomy within HERA C6 was intended to offer insights into the dynamics of self-scheduling and crew collaboration under varying levels of autonomy. It is important to note, however, that compliance with our self-scheduling methodology was not always consistent, and our previous work has highlighted where crews did not use this time fully or as intended [27].

We measured self-scheduling session performance using two metrics: the time participants took to conduct their

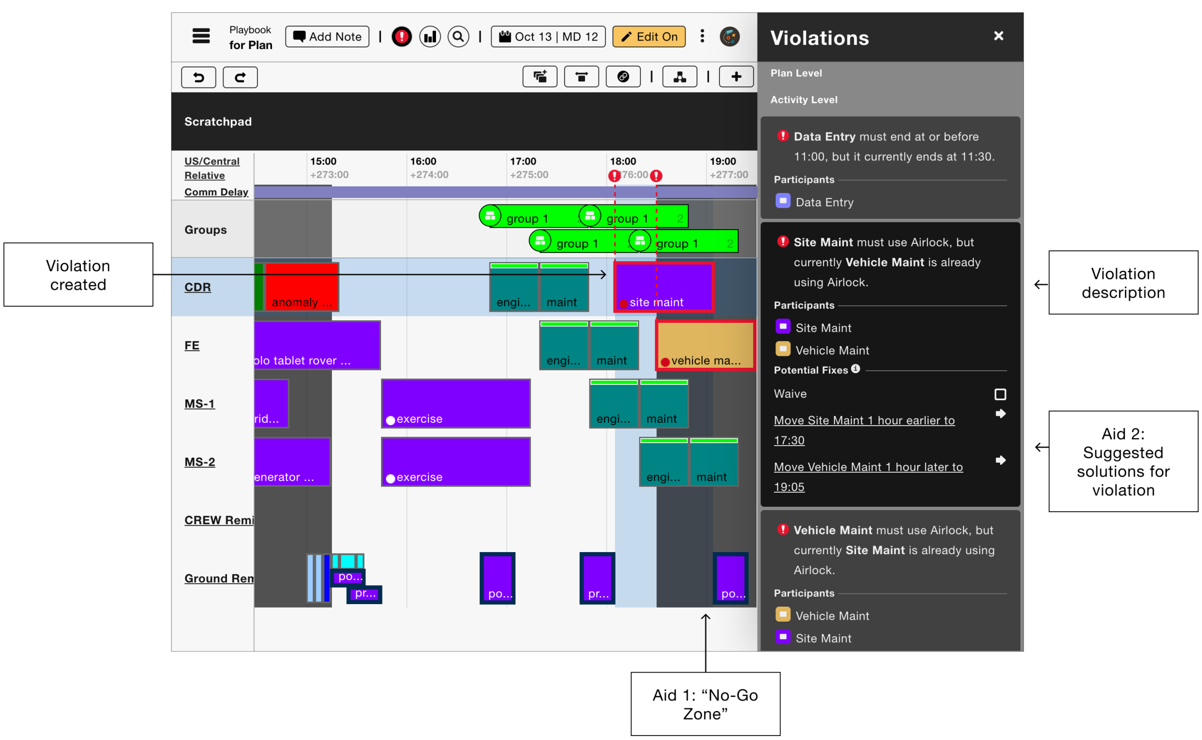


Fig. 2 Example of Playbook's timeline view with the added scheduling countermeasures of no-go zones and potential fixes.

scheduling session and the number of violations the analog crew created during their session. We measured each event: the time between when the crew clicked "Edit On" in the interface and the last time the crew clicked "Edit Off." Typically, participants did all their scheduling within a single session, but the crew occasionally followed this with an additional, shorter scheduling session where they moved only a few activities. We summed the number of violations across all the participant's scheduling sessions. Violations occurred when participants scheduled activities at a time that violated one of the activity's constraints. Each activity could have one or more constraints, including:

- Claim Constraints specify a particular piece of equipment needed for an activity or set of activities (e.g., Activities A and B both need a treadmill, so they cannot be scheduled simultaneously).
- Unary Constraints limit when you can schedule an activity (e.g., you must start Activity A no earlier than 0900 and finish no later than 1030, or both).
- Binary Constraints indicate when you should schedule an activity relative to another activity (e.g., you must schedule Activity A before Activity B).
- Assignment Constraints limit which crew member can complete an activity (e.g., you must assign Activity A to the flight engineer).
- Profile Constraints mean a specific, static resource must be available for the activity. In HERA C6, the profile constraints were only used to limit the day of the activity's execution (e.g., the activity must be completed on Mission Day 7).

Due to the operational constraints of the HERA campaign, each crew member had a unique day to schedule, each with a different number of activities and various amounts and types of constraints. At least one of each constraint type was present on each crew member's scheduled day, and we attempted to select days with an even distribution of constraints. While we tried to choose similar days (e.g., all scheduled days were work days), we could not directly control the number of activities or constraints each crew member had to schedule on their given day.

In this study, we examine the performance of the analog crew and the workload associated with the scheduling process during HERA C6. All participants used Playbook to complete their scheduling sessions. Our analysis focuses on a between-subjects variable of no aid (C6M1 and C6M2, where no additional software scheduling aids were provided) and aid (C6M3 and C6M4, which included scheduling aids). This distinction allows for an evaluation of the impact of these aids on crew performance and scheduling efficiency. The Aid group had two additional countermeasures not present in the No Aid group's version of Playbook; see Fig. 2. These countermeasures, designed to help prevent or resolve Claims, Unary, Binary, and Profile constraints, are described here:

1) No-go zones were displayed as grayed regions that indicated to the user regions of the timeline where activities could not be scheduled without creating a violation. However, no-go zones did not gray out rows (representing crew members), so they did not help resolve Assignment constraints.
2) Potential fixes appeared in the violations tray as one or more scheduling suggestions that would resolve the violation with a single click*.

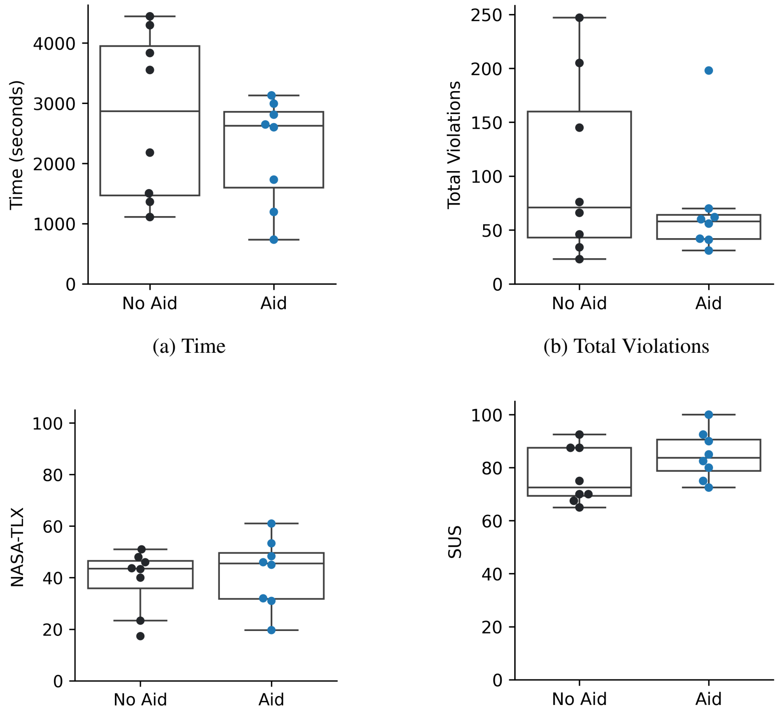
IV. Results

Due to HERA C6's operational limitations, each crew member was only allowed to schedule one day in the timeline, and we have a limited data set to analyze. A preliminary analysis of our data indicated they were not normally distributed, so Mann-Whitney U tests were used to analyze this dataset. Mann–Whitney U tests use a rank-based approach that is effective for small sample sizes and can provide insights without relying on parametric assumptions. A series of tests were conducted to compare participants' performance with aid vs. without aid across four measures: time on task, total violations, NASA-TLX, and SUS. Effect sizes are reported using the rank biserial correlation coefficient (r_{rb}).

We investigated time on task and the total number of violations to evaluate performance. Participants in the Aid group (n = 8) had a mean time on task of 2,230.25 seconds (SD = 894.06, Mdn = 2,624), while those in the No Aid group (n = 8) had a mean time on task of 2,785.25 seconds (SD = 1,391.58, Mdn = 2,866). The difference in time on task between the groups was not statistically significant, $U = 24.0, p = .442$, with a mean difference of 555 seconds and a small to medium effect size (rank biserial correlation, r_{rb} = .25); see Fig. 3a. Participants in the Aid group committed fewer total violations ($M = 70.0, SD = 53.31, Mdn = 58$) than those in the No Aid group ($M = 105.25, SD = 83.98, Mdn = 71$). However, this difference was not statistically significant, $U = 24.0, p = .442$, with a mean difference of 35.25 and a small to medium effect size (r_{rb} = .25); see Fig. 3b.

We investigated NASA-TLX to evaluate workload and the SUS to evaluate usability. For NASA-TLX scores, the Aid group reported a mean of 42.04 ($SD = 13.49, Mdn = 45.5$), whereas the No Aid group had a mean of

*Potential fixes were only used once during the experiment, however, and are not discussed further here.



(a) Time

(b) Total Violations

(c) NASA-TLX

(d) SUS

Fig. 3 Box plots of the four metrics used in this study, measuring performance with (a) time to complete the task and (b) the total violations created, measuring workload with the (c) NASA Task Load Index (NASA-TLX), and measuring system usability with (d) the System Usability Scale (SUS). Box plots show the median and quartile ranges.

39.08 (SD = 12.13, Mdn = 43.5). The difference between groups was not significant, U = 25.5, p = .528, with a mean difference of 2.96 and a small effect size (r_{rb} = .203); see Fig. 3c. The Aid group reported higher SUS scores (M = 84.69, SD = 9.20, Mdn = 83.75) compared to the No Aid group (M = 76.88, SD = 10.67, Mdn = 72.5). Although this difference was not statistically significant, U = 18.0, p = .155, the mean difference of 7.8 suggests a moderate to large effect size (r_{rb} = .438); see Fig. 3d.

The relationships between the four variables, time on task, total violations, NASA-TLX, and SUS, were assessed using Kendall's Tau-b correlation coefficients. Time on task and total violations had a significant positive correlation, τ_b = 0.42, p = .026, indicating that higher time on task was associated with more violations. The other correlations, including those involving NASA-TLX and SUS, were not statistically significant (p > .05). Although none of the differences between the Aid and No Aid groups reached statistical significance, the Aid group exhibited trends toward better performance on several measures. Participants who received aids tended to complete tasks more quickly, reported higher usability scores on the SUS, and committed fewer total violations. The effect sizes ranged from small to moderate, with the largest effect observed for SUS scores, suggesting a potential practical impact of the aids on system usability. Perhaps unsurprisingly, we found that higher task times were correlated with more violations, likely because violations would take the crew some time to understand and resolve.

V. Discussion

We conducted an experiment to determine how the inclusion of scheduling countermeasures (i.e., user interface aids) affected performance, workload, and usability in NASA's HERA C6, a spaceflight-like environment. We provided users with one of two versions of the Playbook interface: the analog crew in M1 and M2 used a baseline interface without aids, while the crew in M3 and M4 were also provided with additional features (i.e., no-go zones and potential fixes). Analysis of the experiment results showed mostly no significant effects, likely because our study was underpowered due

Table 1 Descriptive statistics (mean, median, and standard deviation) for the violations conducted within the scheduling sessions.

		Total	Claims	Binary	Assignment	Unary	Profile
Mean	No Aid	105	52	38	7	8	0
	Aid	70	29	19	16	6	2
Median	No Aid	71	35	14	5	8	0
	Aid	58	21	14	11	5	0
Standard Deviation	No Aid	84	45	52	6	6	1
	Aid	53	23	13	15	6	4

to the mission's operational constraints. Despite the lack of statistical significance, consistent participant performance trends emerged. Participants with the scheduling aids completed their sessions an average of 20% faster than those without them, creating an average of 33% fewer violations. NASA-TLX workload scores increased slightly with the aids, by approximately 3 points, though this is neither significant nor a meaningful change. The countermeasures appeared to be most effective at reducing Claims and Binary violations, with 45% and 51% fewer created, respectively. While Assignment violations increased when aids were introduced, the overall number of violations was still reduced compared to the No Aid group. These aids appear not to have strongly influenced Unary and Profile constraint violations, though they rarely occur for either group of schedulers. We also observed a large decrease in the standard deviation of violations across constraint types. While countermeasures may assist those who are especially error-prone, they seem to have little effect on high performers, indicating that these aids bring all users to a more consistent level of performance. The complete descriptive statistics of the number of violations created by each group are available in Table 1.

By presenting these analyses, this paper aims to contribute to the ongoing discussion on managing crew schedules in long-duration space missions to enhance overall mission success. While this work provides evidence that targeted scheduling countermeasures (i.e., no-go zones) can reduce the occurrence of specific types of constraint violations, the development of additional countermeasures is ongoing. By introducing no-go zones, we inadvertently shifted the prevalence of scheduling constraint violations to Assignment constraint violations. As these no-go zones gray out any temporal portions of the timeline that do not meet the constraint but not the crew assignment aspect of the timeline, the schedulers may have inadvertently believed that those other crew were valid scheduling options. As the current implementation of no-go zones pertains solely to activities' schedulable times, it may have inadvertently distracted users from considering the row-based (i.e., crew assignment) implications of the scheduling. A future implementation of no-go zones could also gray out crew rows that do not meet the crew Assignment constraints. As noted earlier, the potential fixes aid was only used once in this study, which suggests that this feature was not discoverable. We trained participants on this feature, but they may have forgotten it or simply chosen not to use it during their scheduling sessions. Further design work could make this feature more prominent or move it to a different part of the interface.

Despite the potential fixes aid not being leveraged, no-go zones seemed to have driven a considerable increase in Playbook's usability. During the post-mission debriefs, one crew member exclaimed, "No-go zones are awesome!" and system usability rose from an average of 76.88 without aids to 84.69 with aids. Although this difference was not statistically significant, this does mark a significant change as Playbook may now meet NASA-STD-3001, Volume 2, Revision D requirements for system usability [30]. Future usability studies can use the new NASA Modified SUS (NMSUS), developed after this study, to confirm that this requirement has been met. Regardless, this high level of usability aligns with our previous work investigating usability using the User Experience Questionnaire [31]. Altogether, targeted interface countermeasures make Playbook an effective, usable system — one that is well-equipped to support crew self-scheduling in high-stakes environments by helping confront the demands of long-duration space missions.

Acknowledgments

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