Cognitive Impact of a Drone-Assisted Inspection in a Space Analog Mission

Javier Garrido Jiménez

S4791320

Department of Psychology, University of Groningen

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Supervisor: Prof. Dr. Elkan Akyürek

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Abstract

This single-participant case study examines the cognitive impacts of using a non-adaptive human-machine interaction (HMI) system during a drone-assisted environmental inspection in a space analog mission. The research specifically aimed to assess how such interaction affected situational awareness, measured through changes in spatial attention (SA) and visual working memory (VWM). Three experimental conditions were systematically evaluated: A baseline No-Drone condition where an environmental inspection was conducted without HMI support, a Drone condition involving a drone-assisted environmental inspection, and an Emergency condition simulating a high-pressure, drone-assisted inspection task. Cognitive performance metrics were quantitatively evaluated using a visual search task for SA and a delayed match-to-sample task for VWM. Response time and accuracy data were analyzed by calculating EZ diffusion model parameters, and analyzing them descriptively. Results indicated that the Drone condition may have imposed additional cognitive load, as reflected by decreased performance in SA and VWM compared to the No-Drone condition. Conversely, the Emergency condition elicited enhanced cognitive efficiency, likely facilitated by heightened arousal, which countered the cognitive load effects of the HMI system. These findings underscore the cognitive challenges posed by non-adaptive HMIs in space-related tasks and highlight the potential benefits of adaptive system designs that consider the operator's cognitive state and environmental demands. This research contributes to the understanding of cognitive dynamics in human-machine systems within space analog settings, and lays the ground for future studies to explore these interactions with a larger sample and varied HMI configurations.

Keywords: Human-Machine Interaction, Situational Awareness, Space Analog Missions, Spatial Attention, Visual Working Memory.

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Background

Space Research and Psychology

Space flight has for long been subject of scientific inquiry and fascination. Outer space's microgravity conditions, extreme temperatures, lack of resources, and high radiation levels make it an inherently hostile environment for life. Yet humans are increasingly venturing into cosmic exploration. The rationale for space missions is multifaceted, with various goals and motivations driving the endeavor, including geopolitical, technological, and economic incentives. Scientifically, projects such as NASA's Artemis program, which aims to land humans on the lunar south pole by 2025 and establish a permanent manned scientific moon base throughout the next decade, promise significant advancements in space science and human sustainability (Smith et al., 2020; Watson-Morgan et al., 2021).

International space organizations have recently taken giant leaps into astronautics, including India landing the unmanned Chandrayaan-3 on the lunar south pole in August 2023, Japan landing SLIM on the lunar Gruithuisen Domes on January 2024, and the U.S. returning to have presence on the moon after over fifty years with its Odysseus lander in February 2024. All evidence points to a new space race, which allows for the world to envision true interstellar travel. In order to make this vision a more concrete reality, it is essential to further current research into the effects of outer space environments on the human mind.

The emphasis on psychological and cognitive research in the field of space exploration have evolved significantly over time. Initially, psychological sciences were integral to the foundation of space programs: Already between 1957 and 1958, when both sides of the Cold War were launching satellites into orbit, "psychology had an important role to play, [as] is apparent from its inclusion on several new scientific committees to advise on space flight problems” (Grether, 1962, p.93). However, during and after the U.S. Apollo program, most branches of psychology became notably absent from NASA’s research and operational focus, as behavioural requirements started shifting. It wasn’t until over two decades later that, due to the influence of Russian cosmonauts at the space station Mir, NASA started to recognize and invest in the field of behavioural and cognitive health and its links to performance, which opened the door to many kinds of research that were formerly overlooked (Vakoch, 2011).

A new era of collaboration between psychology and space programs was spurred on by the 1987 Committee on Space Biology and Medicine of the National Research Council, in which it was stated that “there is reason to believe that behavioral and social problems will become more frequent as missions become longer and more complex, and as crews become larger and more heterogeneous” (National Research Council, 1987, p.165). Recently, while many have recognized a stigma toward psychology in space programs – perhaps connected to a historical connotation of astronauts being the epitome of human performance, and psychological difficulties being seen as a weakness – the start of a general culture shift for a more open relationship between the two worlds seems to become more and more present in space agencies (Sherriff & Favier, 2016).

Currently, space psychological and cognitive science continue to evolve rapidly. Reviews of psychological factors within space-related missions have shed light onto cognitive shifts experienced by astronauts (Koppelmans et al., 2013). For instance, psychomotor functions, especially spatial orientation, mental rotation and recognition, spatial perception and representation are substantially affected in space (De La Torre, 2014, p.287). Moreover, astronauts face altered physiology and increased exposure to stress, which has been found to impact cognitive and psychological well-being, with stress hormones such as glucocorticoids affecting particularly memory and learning (Lupien et al., 2007; Williams et al., 2009). On top of that, the high workload and the general burden driven by adaptation to extreme living conditions have also been linked to perceptual, cognitive, and psychomotor processes (Manzey, 2000). As space missions become longer and more intricate, including more complex technologies, the need for studying psychological and cognitive variables in specific – and relevant – contexts while addressing research gaps becomes fundamental.

Space Analogs and Psychological Research

The prospects of human life outside of planet Earth necessitate extensive research and planning. In order to facilitate this, space agencies, governments, and research teams – also comprising psychologists – have created on-Earth controlled situations where they can simulate environments akin to a space station, a subterranean habitat on Mars, or a Lunar base. These space analog missions have seen a recent spotlight and aroused interest from academic and professional circles (Heinicke & Arnhof, 2021); examples include the Mars500, organized by the European Space Agency, Russia and China, the HI-SEAS, funded by NASA, or projects such as Asclepios, run completely by students and supervised by space sector professionals (Asclepios.ch, 2020).

In an environment where safety is an essential concern, being able to study and prepare for the "human factor" is not something the field is willing to overlook. This is why outstanding importance has been given to analog research since the beginning of the space age (Hettrich et al., 2015). Being able to study potential astronauts' psychological and cognitive responses to uncommon contexts like microgravity – through head-tilt bed rest tests – (Koppelmans et al., 2013), or isolated and confined spaces – with the reutilization of remote or Antarctic research bases – (Reagan et al., 2012) has allowed furthering the study of psychological space research at a much lower human and economical cost than *in situ* on-orbit testing. At the same time, researchers have recognized substantial difficulties in analog research.

Analog missions do count with numerous limitations. These restrictions are synthesized chiefly by methodological heterogeneity and low sample sizes, together with the commonly self-administrative nature of testing in isolated and confined settings (Casler and Cook, 1999). This is underlined by the inherent differences between space and Earth environments for human behavior. However, these barriers are generally counterweighted by increased accessibility and availability. Furthermore, despite the difficulties of getting close to laboratory conditions, space analog setups offer unique field-testing for psychology and cognitive science, which can counterweight limitations considering the uniqueness of these scenarios, given that data involving behavior and emotions appear susceptible to environmental influence (Calisi et al., 2009). Consequently, over the years, testing and findings from analog missions have proven fruitful in predicting and preparing for actual space missions. Work such as that by Nasrini et al (2020) has allowed to investigate – on Earth – the combined effects of isolation, confinement, and sleep deprivation on cognitive performance and psychomotor vigilance during spaceflight. They did so through the administration of computerized neurobehavioural test batteries during NASA's Human Exploration Research Analog project, and it served to identify, among others, detrimental effects of sleep deprivation on cognition, and hence to refine mission planning before venturing into space. In general, on-Earth studies that addressed psychological and cognitive factors – such as monitoring astronaut mental health, providing psychological training, or refining astronaut selection by highlighting the importance of specific personality traits, psychological stability, and social skills (Manzey et al., 1995; Mesko, 2018; Ursin et al., 1992) – are some of the most influential dissections in the past and present of space research. Considerations like these would not have been obvious in a research environment that did not account for the psychological and cognitive factors in space analogs.

The Emerging Relevance of Human-Machine Interactions in Space

Advancements in human-machine interaction (HMI) are transforming the landscape of technology-driven sectors, notably revolutionizing space missions. The relevance of these interactions in space research is underlined by the need for effective collaboration between humans and robots in mission design (Green et al., 2008). Furthermore, due to their complexity, these types of interactions are never simple to conceptualize, predict, and refine. For example, a non-adaptive machine system needs explicit commandments for interactive tasks with humans, a constraint that hinders the human-machine system's potential capabilities due to a lack of common grounding. The problem is deepened by machine and robotic systems usually being self-contained, with little to no social intelligence. The lack of a social component in their engineering might cause cognitional decrements such as faulty decision-making, lapses in judgment, or a deficiency in problem-solving situations (Huntsberger et al., 2011).

An alternative is to design adaptive machine systems that can interpret, predict, and adapt to human factors such as cognitive or emotional states, or social contexts. In space, these human factors can vary for a variety of reasons. For example, both EVA astronaut suits – utilized chiefly by NASA – and the interior of the International Space Station host a high amount of Carbon Dioxide, which can negatively affect cognition (Kanki et al., 2017; Snow et al., 2019), leading to performance decrements. In space missions, where even the smallest of errors can cause tragedies (Bluth, 1984), the potential for these decrements should be taken into consideration. In the case of a machine such as the European Robotic Arm (Cruijssen et al., 2014), when assisting or collaborating with an astronaut on a task requiring precise mental capacities such as memory or attention, the device should be able to recognize and adapt to, for instance, decreased astronaut cognitive capacity caused by the commonly altered CO_2 levels. The machine could do this by, for instance, taking over workload or by halting the task safely if astronaut stress or overall risks become too high. Furthermore, the complexity of operating machinery and robotics in space can also in itself lead to the deterioration of cognitive and perceptual-motor performance (De la Torre et al., 2014). Even though advancements in HMI technologies and machine learning promise significant improvements in this regard, missions will realistically continue to implement both adaptive and non-adaptive HMI systems (Bartone et al., 2019). Hence research of both these types of categories of HMI setups continues to be crucial.

Essentially, the study of HMI in the context of space missions has become increasingly vital. Research highlights the importance of understanding the cognitive impacts of environmental factors and technology on astronauts and the necessity of designing systems that support both human expertise and machine functionality. Interdisciplinary collaboration, informed by psychological methodologies, is key to enhancing operational resilience in space missions. By integrating insights from psychologically sensitive studies in space and space analog missions, future endeavors can better address the complexities of human-machine dynamics in space exploration.

Rationale of the Current Study

The APICES Space Analog Mission

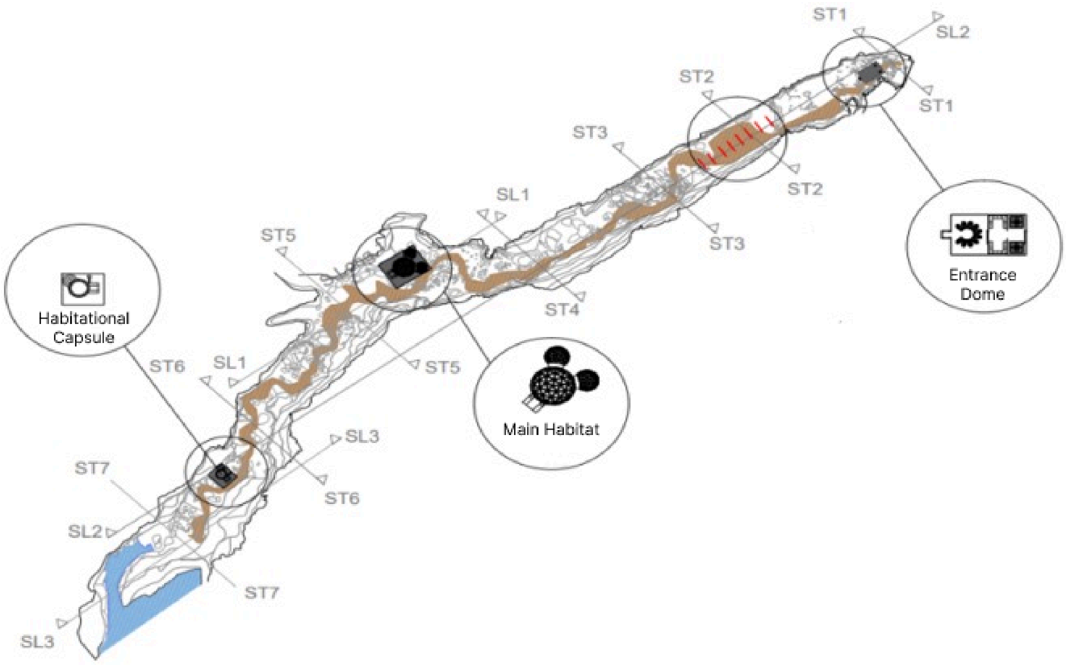
The current study took part during a cave-based space analog mission. The venue was a large cave system in northern Spain, selected for its geological and environmental resemblance to Lunar and Martian lava tubes, which are regarded as the most likely locations for upcoming human colonial habitats (Cushing, 2012; Ponce et al., 2021), as they act as a natural shield for radiation, micrometeorites, extreme temperatures, and offer proximity to natural resources.

The mission involved six crew members and seven mission controllers, and was aimed at conducting experiments while standardizing procedures for human factors research and technological testing in this site. While living in the cave's isolated and confined conditions for six days, crew members conducted multidisciplinary research and tasks involving robotics, communication systems, biome sampling, and speleology involving cave climbing. Any activity that took place outside the habitat was considered an extra-vehicular activity (EVA) and involved a simulated airlock (de)compression procedure to exit and enter the habitat, and a full analog astronaut suit donning and doffing, including gear and analog helmets. During the mission, crew members followed Martian time and, accordingly, a 25-hour day schedule. Communications with mission control were subject to Earth-Mars time delay, and their diet consisted of lyophilized meals and emergency bars. Water use was limited to 4 liters per person, per day, for all purposes. It all was aimed at rigorously replicating factors of a real space mission as closely as possible.

The crew lived in a dome-like habitat located approximately in the center of the nearly two-kilometer long cave (see Figure 1). This station was designed to closely replicate future Martian habitats in terms of isolation, environmental conditions, and resource limitations. It is equipped with living quarters, research laboratories, and spaces suited for simulating EVAs, such as a cylindrical airlock (see Elorzaa et al., 2020). Key features of the dome include a solar-based power system, and life support systems, designed to ensure the sustainability of long-duration missions through recycling and regeneration of resources, such as water and air. By providing a realistic and controlled environment for studying human behavior and technology performance, this location offered unique opportunities for researching psychological and human factors in the context of space analog missions.

Figure 1

Cave map showcasing the main habitat location at the center of the cave (De la Torre, 2022).



One of the aims of this mission was to conduct tests in the context of HMI, and one such test was to conduct a drone-assisted environmental inspection. In this task, a crew member had to conduct an EVA and make use of a drone (see Methods section for hardware specifications), to inspect and gather environmental footage of specific areas around the habitat and the cave walls. In order to address the already stated gap in cognitive research during analogs, in the current study we tested visual working memory (VWM) and spatial attention (SA) via computerized tests in the context of the drone-assisted task.

The selection of these specific cognitive tests was guided by a critical factor for decision-making and performance in contexts such as operating complex HMI systems or aviation (Endsley & Bolstad, 1994) known as situational awareness, which refers to the ability to accurately perceive, understand, and predict the relevant elements in the environment within a volume of time and space (Endsley & Garland, 2000). Working memory emerges as an important component, as it has been correlated with situational awareness performance (Sohn & Doane, 2004) and sensitivity in pilots (Cak et al., 2020). VWM is a specific and inherent part of working memory that deals with the temporary storage and manipulation of visual and spatial information. SA is another critical component in situational awareness, representing the ability to inhibit irrelevant stimuli from the environment and focus our attention on relevant signals (Krauzlis et al., 2013). It is a fundamental predecessor to the allocation of attentional resources to a specific region in the environment (Carrasco, 2018). Moreover, SA has a direct link to performance; for instance, research in the Israeli Air Force found that selective attention capacity was positively associated with pilot success (Gopher & Kahneman, 1971). Furthermore, Wickens et al. (2010) highlighted the mediating role of situational awareness in optimizing routine human-automation performance and managing scenarios of automation failure. Non-adaptive HMI systems, such as the drone setup used in our experiment, impose increased cognitive load and deplete the attentional resources of the operator (Ramakrishnan et al., 2021). In the present case study, we aimed to investigate the post-task effect of a non-adaptive HMI system (in this case the drone) on SA and VWM using, respectively, a visual search and a delayed match-to-sample computerized task.

Objectives and Research Question

Shifts in working memory and spatial attention related to HMI, linked to consequent alterations in operator situational awareness, may exert notable impacts on task performance. These effects have not been thoroughly tested in the context of space analog missions, yet they can have direct consequences for crew and machine safety, and the performance of HMI systems. To address this, our cognitive research focuses on answering a pivotal question: Are there observable differences in post-task (1) VWM and (2) SA in a drone-assisted environmental inspection versus in an inspection without the drone? Additionally, we included a third experimental condition involving a drone-assisted environmental inspection during a simulated emergency scenario, in order to explore effects caused by time-sensitive high-stakes contexts, which play a vital role in space missions. By addressing this, our study aims to explore the potential benefits of researching these cognitive variables in the context of space analogs, specifically during HMI tasks for environmental inspection.

Methods

Participant

This case study focuses on a single participant, who is a middle-aged individual from a highly specialized profession within the field of space exploration. For confidentiality reasons, specific details that might reveal the identity of the participant, such as exact age, gender, and detailed professional role, are withheld. This individual was selected for the study based on their unique occupational background and the relevance of their experience to the research questions concerning spatial attention, visual working memory, and human-machine interaction in the context of astronautics. The participant provided informed consent for their involvement in this study, ensuring they were fully aware of the study's nature, its objectives, and their rights as a participant. This research was carried out in strict accordance with ethical standards and was formally approved by the Ethics Board of Masaryk University.

Materials

In this experiment, a 15.6" laptop with an Intel Core i5-9300H processor with a refresh rate of 60GHz and an 8-bit color depth was used to present the tests. Resolution was set at 1920 by 1080 pixels. Responses were recorded with the built-in keyboard and a Bluetooth wireless optical mouse with a 1000 DPI sensor sensitivity. The computerized tests were programmed with OpenSesame 3.3.9 (Mathôt et al., 2012a), and the program was run on Windows 10.

A testing environment was set up strategically off-center of the dome-like habitat, closer to the curvature of the room's wall. This positioning was chosen to ensure minimal distractions and to provide a semi-isolated space despite the unavoidable presence of the other crew members in the same dome, enhancing as much as possible the focus and comfort of the participant during the test.

Procedure

We administered both spatial attention (SA) and visual working memory (VWM) computerized cognitive tests to the participant consecutively and in randomized order after each of three conditions (described below). The conditions were the independent variables, and the dependent variables were accuracy and response times in a visual search (measuring SA) and a delayed match-to-sample (measuring VWM) task.

Conditions

No Drone condition. This was designed as a baseline condition and took part during the third day of confinement. In this condition, the participant took both cognitive tests after taking part in a simulated extra-vehicular activity (EVA) that did not involve the operation of a drone or any other robotic machinery. The EVA was preceded by donning and a simulated ten-minute depressurization airlock procedure and consisted of a cave biome inspection and a sampling task, where the participant together with two other crew members followed mapped instructions to inspect and collect biome from different areas of the cave. Following the completion of the task, the participant and his team underwent a simulated ten-minute airlock pressurization procedure. After this process, the participant came back inside the habitat and was given time to doff their gear and suit and change into their personal clothes. Within twenty minutes, the experimenter welcomed the participant to the experimental desk setup, where the participant, after sitting down, took both cognitive tests using the laptop and the mouse, at approximately 60 cm viewing distance from the screen.

Drone condition. In this condition, which took place on the second day of isolation, the participant underwent the same preparatory donning and airlock procedure as in the previous condition. During the EVA, the participant and his team (composed of the same members as in the previous conditions) first walked to a predetermined location inside the cave following mapped instructions. Next, the participant assembled the drone, flew it to the assigned location, and inspected the habitat through the drone controller's display while taking video footage of key habitat sections. After completing the inspection, the participant came back inside the airlock with the other crew members. Next, the standard ten-minute simulated airlock compression procedure and doffing followed. After this, the experimenter recreated the administration of the computerized cognitive tests, which the participant took in the same place using the same setup as in the NoDrone condition.

Emergency condition. The third and last condition was designed as an emergency scenario and took place on the fourth day of isolation. It involved the use of the drone to respond to the emergency and the subsequent administration of both cognitive tests after an emergency EVA. In this scenario, an unexpected alarm signaled to the participant and the rest of the crew a pressure loss within the habitat, prompting mission control to brief the crew on an emergency EVA to assess and repair habitat damage. The participant, assigned as the drone operator, was tasked to locate and document two specific damages within a 40-minute window, using the drone. Following the EVA and the standard ten-minute airlock compression simulation before entering back into the habitat, the participant then proceeded after changing attire to undergo the same experimental protocol applied in the prior conditions.

Cognitive Tests

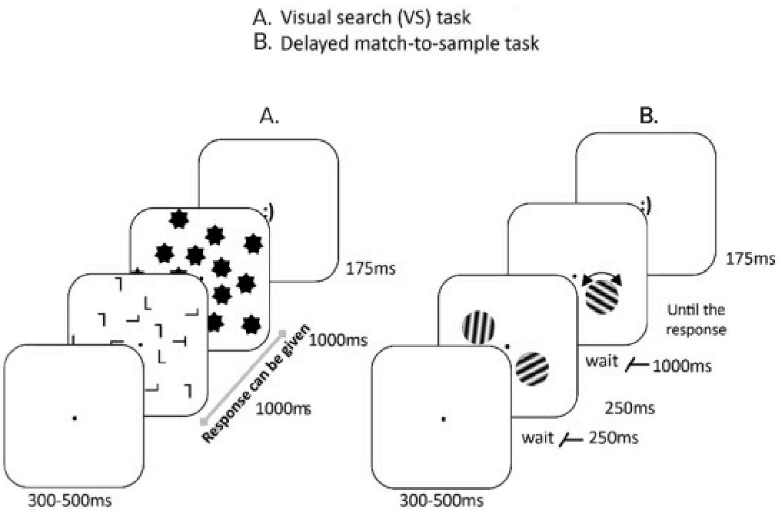
Visual Search

We assessed spatial attention using a computerized visual search task (Figure 1A). We followed the test design by Altınok et al. (2023). Stimuli consisted of a fixation dot, search array, mask, and feedback screen presented successively on a light gray background. On the search array, symbols including the target, which consisted of the letter T, were distributed evenly across the screen. Each trial contained a different, randomized number of distractor symbols: five, seven, or nine. The distractors were the letter L. Both target and distractor symbols appeared in black (RGB 0, 0, 0), in 10 pt. size; 28 by 60 pixels. The letters' orientation was either 0°, 90°, 180°or 270°, evenly distributed and randomized across trials. On the search array, all symbols were distributed across an invisible concentric circle within 5.05 degrees of visual angle.

As per the test-specific procedure, we also followed the experimental lines designed by Altınok et al. (2023). In our study, the visual search task had 612 trials (324 for the Drone condition, 144 for the NoDrone condition, and 144 for the Emergency condition). The participant was allowed to have a break between blocks of trials, although he did not do so. Each block of trials started when the participant pressed the spacebar. After that, the fixation dot was shown for 300-500 ms, followed by the search array, which lasted 1000 ms and was covered by a mask for the following 1000 ms. The participant was instructed to report the orientation of the target letter T using the arrow keys on the keyboard. After each response, a feedback screen followed for 175 ms, which consisted of either a happy or unhappy smiley, according to accuracy. The next trials followed after 250-300 ms intervals until all test trials were completed.

Figure 1

*(A) The visual search task showing fixation dot, search array with 14 distractors, mask, and feedback. (B) Example of a two-item condition within the delayed match-to-sample task (*Altınok et al., 2023).



Visual Working Memory

A delayed match-to-sample task (Figure 1B) was used to assess visual working memory. Following the test design by Altinok et al. (2023), stimuli consisted of memory items (Sine-grating Gabor patches of 2.2° of visual angle on an invisible circle of 6.46° visual angle) and a feedback screen presented successively on a light grey background. Each trial contained a randomized number of memory items; one, two, or three. As per the test-specific procedure, we also followed the experimental lines designed by Altinok et al. (2023); in our study, the visual working memory task had 456 trials (252 for the Drone condition, 108 for the NoDrone condition, and 96 for the exploratory Emergency condition). The participant was allowed to have a break between blocks of trials, although he did not do so. Each block of trials started when the participant pressed the spacebar or clicked the mouse. After that, the fixation dot was shown for 300-500 ms, followed by a blank interval, which lasted 250 ms.

Each item was presented with a random orientation (1-180°) in each trial. After a one-second delay, one of the items appeared in one of the previous item locations but in a different, random orientation, but at least 15° from the actual orientation of the target item. The participant had to reproduce the item's target orientation as accurately as possible by adjusting it with the Bluetooth mouse. After each response, a feedback screen followed for 175 ms, which consisted of either a happy or unhappy smiley, according to accuracy. The feedback was positive if the error was less than 15°, and negative otherwise.

Data Analysis and Coding

In this study, we employed the EZ diffusion model (Wagenmakers et al., 2007) to analyze cognitive performance across different experimental conditions. The EZ diffusion model is a simplified version of the 'full' diffusion model (Ratcliff, 1978), and it is a useful tool for analyzing data from decision-making experiments (Groulx, 2020), and is particularly relevant in this case due to its ability to be applied to data-sparse situations to facilitate individual subject analysis (Wagenmakers et al., 2007). The EZ diffusion model utilizes the average response time, response time variability, and accuracy rate to calculate three key parameters that map onto cognitive processes. These parameters are (1) drift rate, which reflects the speed of information processing, (2) boundary separation, which represents the degree of caution exercised in making a response, and (3) non-decision time, which informs about the time allocated to processes other than decision-making (van Ravenzwaaij et al., 2017), which are usually categorized into either encoding or motor processes (Weindel et al., 2021).

Our analysis began with preprocessing the raw response time and accuracy data from the visual search and visual working memory tasks. By adopting the EZ diffusion model framework, we transformed these conventional metrics into more nuanced indicators of cognitive processes. This transformation involved calculating the mean accuracy and response times, as well as response time variances for correct responses under each condition (No Drone, Drone, Emergency) separately for each cognitive task. Following this, we applied the EZ diffusion model equations to estimate the parameters for each participant and condition. Lastly, we descriptively compared differences across conditions to observe how they differed in each of the parameters. By applying the EZ diffusion model, we aimed to uncover information on the cognitive mechanisms underlying performance across experimental conditions compared to baseline.

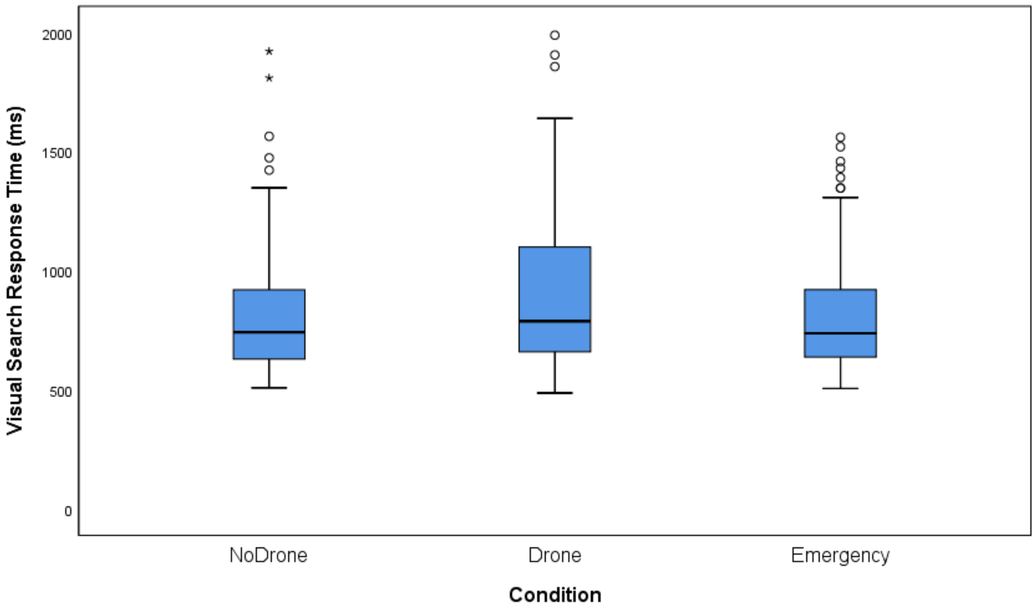
Results

Spatial Attention

Response time distributions for the visual search task revealed some differences across conditions (see Figure 1). After we removed incorrect responses from the data set (19 trials, equal to 3.1% of trials), results showed a mean response time of 821 ms (SD = 259) in the No-Drone condition, in contrast to a higher mean for the Drone condition of 899 ms (SD = 304) indicating slower reaction times in the latter. Response time was the fastest in the Emergency condition with a mean of 818 ms (SD = 238).

Figure 1

Response times for each condition on the visual search task.



Note. Boxplots show the middle 50% of the data, the black line within each box indicates median response times. Whiskers represent 1.5 times the interquartile range. Dots represent singular data points that extend beyond 1.5 times the interquartile range.

In order to apply the EZ diffusion model, we first calculated mean response time, response time variance, and accuracy for each condition. The results are listed in Table 1.

Table 1

Mean response time, response time variance, and accuracy for each condition on the visual search task.

Condition	Response Time Mean (in seconds)	Response Time Variance (in seconds-squared)	Accuracy (proportion correct)
No Drone	0.82	0.09	0.97
Drone	0.89	0.09	0.96
Emergency	0.82	0.05	0.99

We then applied the EZ diffusion model (Wagenmakers et al., 2007) to compute model parameters across the three experimental conditions, as detailed in Table 2. Descriptive analysis revealed variability in the drift rate (v), which reflects the speed of information accumulation. Specifically, the Emergency scenario showed a higher drift rate ($v = 0.25$) compared to the No-Drone ($v = 0.19$) baseline condition, suggesting more efficient information processing under high-pressure situations. In contrast, the Drone condition ($v = 0.18$) was associated with the lowest drift rate, indicating potential reductions in cognitive processing efficiency, possibly due to distraction or increased cognitive load. Furthermore, the boundary separation (a) metric, indicative of the decision threshold, was nearly identical in the Drone (*a* = 0.17), Emergency (*a* = 0.18), and NoDrone conditions (a = 0.18), implying a similar decision-making approach and criteria strictness across all cases, with only a slightly lower decision threshold in the Drone scenario. Notably, the shortest non-decision times (T_{er}), which may encompass processes such as perceptual encoding or motor response preparation, were observed in the No Drone condition (T_{er} = 0.39) The longest non-decision times were found in the Emergency condition (T_{er} = 0.47), and the Drone condition (T_{er} = 0.46). Effects on the EZ diffusion parameters across conditions are displayed in Figure 2. In sum, the results show indices of a possible small impact of drone-related cases and emergency scenarios on cognitive processing efficiency in this particular participant, as quantified by EZ diffusion model parameters.

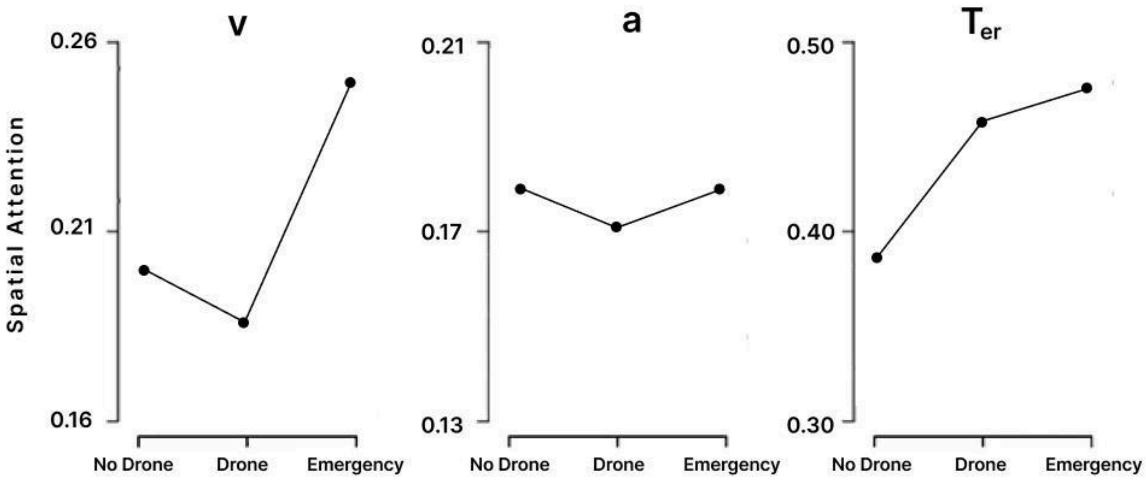
Table 2

EZ diffusion model parameters for each condition on the visual search task.

Condition	Drift Rate (v)	Boundary Separation (a)	Non-Decision Time (Ter)
No Drone	0.19	0.18	0.39
Drone	0.18	0.17	0.46
Emergency	0.25	0.18	0.47

Figure 2

Effects of condition on drift rate (v - left panel), boundary separation (a - middle panel), and non-decision time (T_{er} - right panel) on the spatial attention task.

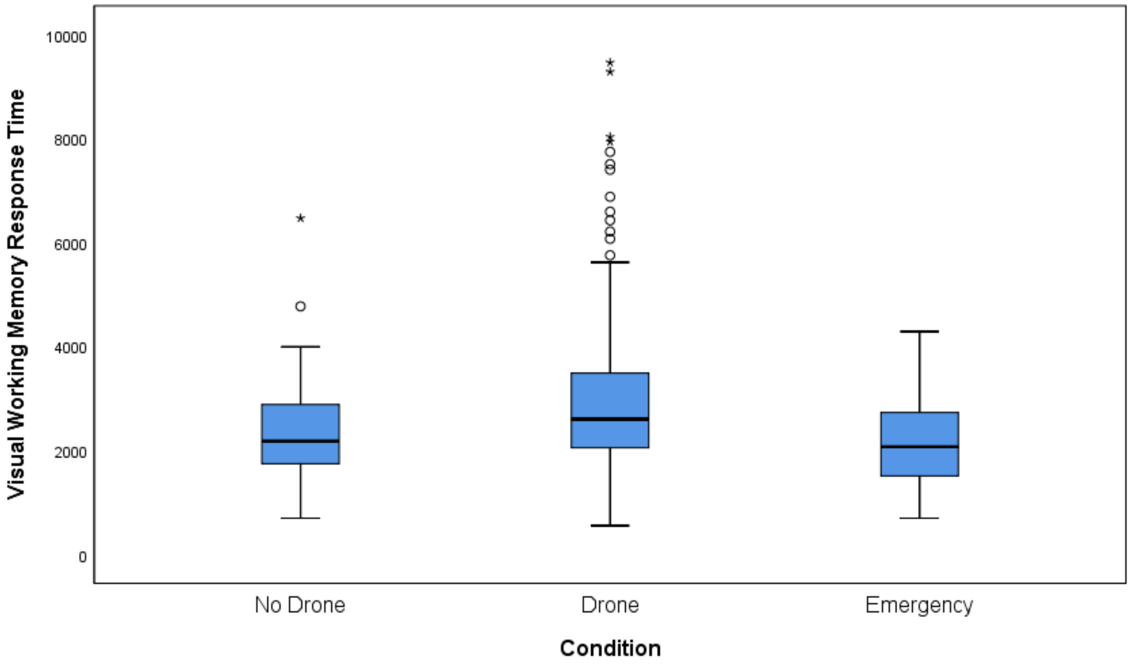


Visual Working Memory

The effects of condition on visual working memory were analyzed by first observing the impact of the three conditions (No-Drone, Drone, and Emergency) on response times and accuracy in the delayed match-to-sample task. For this, inaccurate responses were filtered out from the data set (35 trials, equal to 7.67% of trials). The resulting boxplots are shown in Figures 3 and 4. In the No-Drone condition, the accuracy was 96%, and the mean response time was 2348 ms (SD = 846). In the Drone condition, accuracy was the lowest at 89%, and the the response time mean increased to 2938 ms (SD = 1485). The Emergency condition had an accuracy of 96% and the lowest mean response time at 2184 ms (SD = 878).

Figure 3

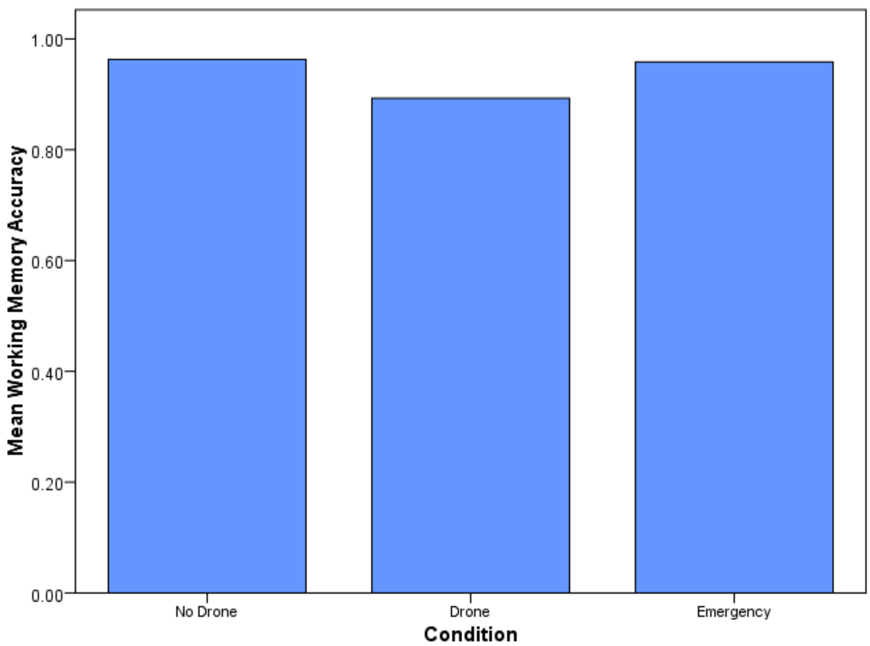
Visual Working Memory Response Times for each condition.



Note. Boxplots show the middle 50% of the data, the black line within each box indicates median response times. Whiskers represent 1.5 times the interquartile range. Dots represent singular data points, and asterisks denote data points 3 times beyond the interquartile range.

Figure 4

Accuracy by condition on the Visual Working Memory Task.



Next, to apply the EZ diffusion model we calculated for each condition the mean response time, response time variance, and accuracy. To clarify, accuracy for each trial was determined using the formula 100 - [(100 × degrees of error)/90] (Altinok et al., 2023). Only trials with an accuracy higher than 80% were considered accurate. The results are listed in Table 3.

Table 3

Mean response time, response time variance, and accuracy for each condition on the delayed match-to-sample task.

Condition	Response Time Mean (in seconds)	Response Time Variance (in seconds-squared)	Accuracy (proportion correct)
No Drone	2.34	0.72	0.96
Drone	2.93	2.20	0.89
Emergency	2.18	0.77	0.96

We then computed the parameter values following the EZ-diffusion model (Wagenmakers et al., 2007). Parameter estimates derived from the EZ diffusion model algorithm are presented in Table 4. The model again estimated the drift rate (*v*), boundary separation (*a*), and non-decision time (T_{er}) for each condition. The resulting parameters reveal distinct cognitive processing profiles across conditions. Drift rates, indicating the speed of information accumulation, showed an identical drift rate in the Emergency ($v = 0.11$) and the No Drone ($v = 0.11$) condition, suggestive of consistent information processing even under stress. However, similar to the spatial attention results, the Drone condition demonstrated the lowest drift rates ($v = 0.06$), indicating a potential distraction or cognitive load effect. Next, boundary separation values, which reflect the decision threshold, were also markedly higher in the Drone condition (a = 0.32) as compared to No-Drone (a = 0.29) and Emergency (a = 0.29), implying increased cautiousness or stricter decision criteria in this scenario. Non-decision times were shortest in the Emergency condition (T_{er} = 0.94), which may reflect a compensatory mechanism in response time due to the pressure imposed by the time-sensitive high-stakes scenario. The Drone condition (T_{er} = 0.99) also shows a shorter non-decision time when compared to the No Drone baseline condition (T_{er} = 1.14). Effects on the EZ diffusion parameters across conditions are visually displayed in Figure 5. In sum, the results suggest that introducing a non-adaptive human-machine system in the environmental inspection, as well as emergency elements, may affect specific cognitive processes.

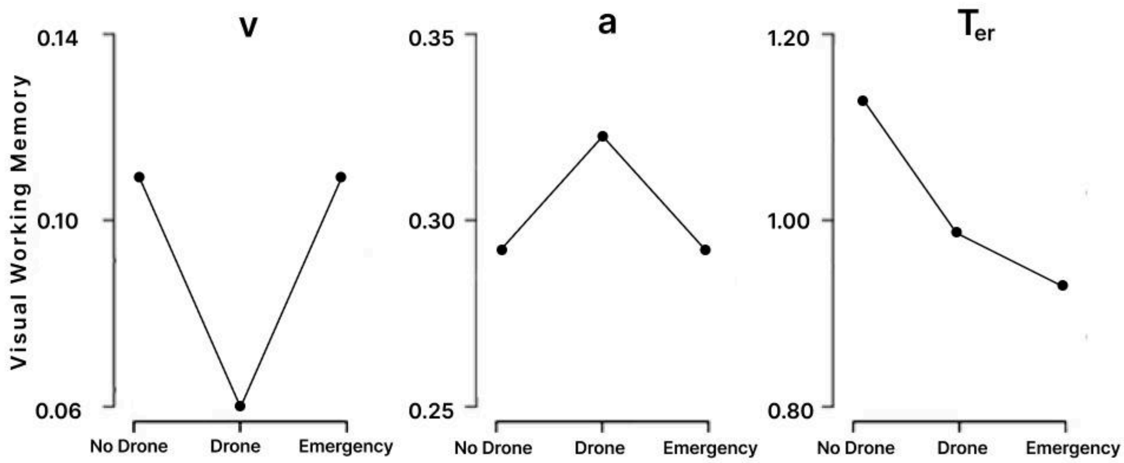
Table 4

EZ diffusion model parameters for each condition on the delayed match-to-sample task.

Condition	Drift Rate (v)	Boundary Separation (a)	Non-Decision Time (Ter)
No Drone	0.11	0.29	1.14
Drone	0.06	0.32	0.99
Emergency	0.11	0.29	0.94

Figure 5

Effects of condition on drift rate (v - left panel), boundary separation (a - middle panel), and non-decision time (T_{er} - right panel) on the visual working memory task.



Discussion

Spatial Attention

Probe Reaction Times

In the current study, we found an observable pattern of variability in spatial attention response times across conditions. More specifically, mean response time was slowest for the Drone condition (899 ms), as compared to the baseline No-Drone condition (821 ms). Comparatively, the Emergency scenario showed the fastest mean response time (818 ms). Although we cannot draw direct inferences, these slower times in the Drone condition are consistent with previous findings from Engstrom et al. (2021), which came to the conclusion that in the case of car driving, cognitive load impairs non-automatized aspects of operation relying on cognitive control. On a similar line, Linnell & Caparos (2011) conducted a series of cognitive experiments that suggest a link between cognitive load and spatial attention. It is then plausible that the introduction of the non-adaptive drone system resulted in higher complexity and increased cognitive load (see e.g. Hennings et al., 2021; Ramakrishnan et al., 2021), which could explain the slower reaction times.

Regarding the faster response times in the Emergency condition, previous research by Reddi & Carpenter (2020) looked at saccades and decision-making in order to study the influence of urgency in decision times, and they found that both urgency and expectations affect how quickly we make decisions, with urgency being linked to faster responses. Despite potential cognitive load from the drone, urgency likely inhibited the workload effect, resulting in quicker responses.

In summary, these results suggest that increased cognitive load from the drone slowed SA response times, while urgency in the Emergency condition sped them up. However, space analog missions involve unique stressors not present in typical laboratory HMI studies. Further research is needed to make more conclusive statements.

EZ Diffussion

Even though traditional statistical testing was not applicable due to the case study design, diffusion model methods allowed us to descriptively analyze variability in parameters across conditions. In this regard, we used the EZ algorithm, as it has been shown to provide the best fitting parameters in applied cases such as this one (see e.g., Schmiedek et al., 2007; van Ravenzwaaij et al., 2011; Wagenmakers et al., 2007). Even though it has previously been used mainly in two-choice decision tasks, since our accuracy levels are high, we make the simplifying assumption that all wrong responses are clustered into a single category.

Drift Rate (*v*)

Firstly, calculations of the drift rate parameter across conditions revealed a lower value in both No-Drone ($v = 0.19$) and Drone ($v = 0.18$) conditions, which suggests that the cognitive processing speed was similar in these two cases. This is in relative comparison with the Emergency condition, which revealed a higher drift rate parameter ($v = 0.25$), suggesting that the quality of evidence or the speed/efficiency of cognitive processing may have improved significantly in the participant under pressure. Overall, this is consistent with the previously discussed findings by Reddi & Carpenter (2020) on urgency being linked to faster reaction times. This could reflect an adaptive cognitive efficiency response to urgency in a scenario where faster decision-making was crucial.

Boundary Separation (*a*)

Boundary separation parameters were nearly identical across all conditions. This reflects an equally cautious approach to decision-making (Starns & Racclift., 2010) in the spatial attention tests following the three different scenarios. This uniformity suggests a general strategy in this particular participant to prioritize accuracy over speed, independently of the complexity or urgency of the condition.

Non-Decision Time (*Ter*)

Non-decision time refers to the total response time that is not directly involved in the decision process itself (Weindel et al., 2021). Here, the shortest non-decision time was in the No-Drone condition (*Ter* = 0.39), indicating a streamlined process at baseline without the added complexity of the drone system. This suggests that the participant executed the tasks with less time spent on peripheral processes, possibly due to the absence of additional cognitive load or urgency/stress. In contrast, the highest non-decision times were found in the Drone (*Ter* = 0.46) and Emergency conditions (*Ter* = 0.47). This suggests that the urgency and complexity of the situations also increased the time required for task-related cognitive processes that are not part of core decision-making, such as encoding or motor responses.

The increased non-decision time in the Drone and Emergency conditions seem to relate to previous results from Weindel et al. (2021), who discussed the influence of the speed-accuracy tradeoff (SAT) on non-decision processes. Their findings indicate that prioritizing speed over accuracy leads to a decrease in non-decision times. In our study, the Drone and Emergency conditions showed an increase, rather than a decrease, in this parameter. This discrepancy may be due to our participant prioritizing accuracy rather than speed, aligning with a previous study by Balci et al. (2011) where participants adjusted their SAT to favor accuracy over reward rate and performance. Alternatively, an additional non-decision stage may be present in accuracy-enhancing conditions; this would be consistent with Weindel et al. (2021) who observed that the processes of encoding and motor latencies in the Drift Diffusion Model (Ratcliff & Tuerlinckx, 2002) do not account for all effects of SAT manipulations.

Taken together, this suggests a nuanced interpretation where stress and complexity might have overridden the typical SAT effects, leading to prolonged peripheral processes. Alternatively, the response processes of the participant – who is trained in emergency and complex military aviation operations – may have been different than in participants from the laboratory-based Weindel et al. (2021) study. Further research incorporating EZ parameters is needed in order to formulate more conclusive statements.

Working Memory

Accuracy and Probe Reaction Times

Results on accuracy and response times in the VWM task also showed distinct cognitive processing patterns across the three conditions. First, the No-Drone baseline demonstrated high accuracy (96%) and moderate mean response time (2348 ms), reflecting a stable and undistracted state. On the other hand, the Emergency condition maintained high accuracy but had a faster mean response time (2184 ms), possibly due to a heightened state of alertness, which could have resulted in a speeding of the motor system, or alternatively in enhanced memory retrieval speeds and overall cognitive efficiency. This mirrors the SA task results and is aligned with the previously discussed evidence in the study by Reddi & Carpenter (2020) on urgency speeding up reaction times, although the exact mechanisms remain unknown.

In contrast, the Drone condition showed decreased accuracy (89%) and the slowest response time mean (2938 ms), likely due to increased cognitive demands imposed by operating the drone. This is consistent with evidence from Engstrom et al. (2021) on cognitive load selectively impairing non-automatized aspects of operation relying on cognitive control, considering that working memory is a key aspect of cognitive control (Draheim et al., 2016).

EZ Diffusion

Drift Rate (*v)*

Drift rates were lowest in the Drone condition (*v* = 0.06), suggesting impaired information processing efficiency possibly due to a cognitive load effect. This is in contrast to the No-Drone and Emergency scenarios which showed identical drift rates (*v* = 0.11). This is in contrast to the SA results where the Emergency values were higher than baseline., which may suggest that despite clear neural overlaps between working memory and spatial attention (LaBar et al., 1999), their functional differences may be affected differently by urgency and cognitive load. Further research is needed in order to understand these differences and the mechanisms behind them.

Boundary Separation (*a*)

Boundary separation values were highest in the Drone condition (*a* = 0.32), reflecting increased decision caution. This is in contrast with the No-Drone and Emergency conditions which showed lower, identical boundary separation (*a* = 0.29). Overall, the elevated decision caution in the Drone condition is somewhat consistent with previous research by Otto et al. (2013), whose findings suggest that stress impairs working memory and sophisticated choice strategies. The Emergency condition's similarity to baseline despite its stress and urgency context is uncertain and highlights the limitations of the single-subject design.

Non-Decision Time (*Ter*)

Non-decision time was shortest in the Emergency condition (*Ter* = 0.94), indicating minimized time spent on processes unrelated to decision-making, such as encoding or motor preparation. This is in contrast with the SA results, where *Ter* was longest in the Emergency condition. This may reflect a prioritization of speed over accuracy, as discussed by Weindel et al. (2021). However, it remains unknown as to why the participant would have switched from prioritizing accuracy in the SA task, to prioritizing speed in the VWM one. An alterative explanation could again be linked to an unknown non-decision process beyond the traditional encoding and motor latencies. These results further point towards a mixed interpretation where stress, situational changes and cognitive traits and states of our participant could have led to a complex interplay.

Limitations

This case study was subject to a number of limitations. Starting with the single-subject design, which inherently limits generalisability, followed by the lack of either a control condition or other comparison participants going through the same experimental design. Furthermore, the nature of the cognitive assessments might have introduced learning effects. Although the sequence of the tests was randomized to mitigate this, the conditions' order couldn't be altered due to logistical limitations and mission requirements. This situation may have resulted in the participant becoming accustomed to the tests, and improving performance with time. Following that, the nature and size of the analogue habitat did not allow for a fully isolated room where the participant could take the tests under laboratory conditions. This presents the possibility of biased results due to external distractors such as background conversations by other crew members, and the inability to control for other unknown environmental distractors. Lastly, the nature of the EZ diffusion parameters analysis lacks the possibility for inference or significance tests, limiting our analysis to descriptive observations.

Conclusion

Despite the limitations, the findings of this case study provide insights into the cognitive impacts of using a non-adaptive HMI system during this drone-assisted habitat inspection in a space analog mission. The results hint in a novel way at how Drone-assisted and Emergency scenarios could uniquely influence situational awareness by impacting spatial attention and working memory and lay ground for future investigation on the cognitive impact of HMI systems on operators in analog missions.

Our study found observable differences in post-task VWM and SA in the Drone and Emergency conditions compared to baseline. This is important because it may imply consequences on attentional and memory-based tasks that follow scenarios involving urgency and cognitive workload alterations. The differences in results between attention and memory, especially in non-decision times, may partially be explained by the VWM tests engaging more internal cognitive processes like memory encoding and retrieval, which are less influenced by external urgency and sensory processing. This pattern also highlights the idea that there may be an additional non-decision stage besides encoding and motor latencies (Weindel et al., 2021). Taken together, the results underscore the importance brought to light by previous research (see e.g., Adams, 2015; Bazzano et al., 2017) of considering cognitive load and situational demands when designing and implementing technology such as drone or aerial systems in high-stakes environments. Enhancing HMI adaptability could potentially mitigate negative cognitive impacts and improve operational efficiency and safety in complex settings such as space and space analog missions.

Further research with a larger participant pool and more controlled conditions is needed to validate these results and refine our understanding of cognitive dynamics in similar high-demand operational contexts. Additionally, future studies that combine post-task test data with intra-task real-time data such as physiological or EEG signals could greatly enrich our knowledge in this area. Ultimately, this would help in developing safer and more effective cognitive support systems and HMI designs that are better tailored to the needs and limitations of human operators in extreme environments.

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