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Adaptive Task Reallocation for Lunar Exploration: Cognitive Load Management in VR to Enhance Human-Computer Collaboration

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ABSTRACT

In lunar exploration, astronauts' cognitive load critically impacts the efficacy of Human-Computer Collaboration (HCC). Effective management of cognitive load is essential for lunar mission success. Current research on HCC cognitive load primarily focuses on post-hoc evaluation, failing to leverage real-time assessment and quantitative outcomes, thus misaligning with actual mission demands. Given the interdependence between machine intelligence levels and astronauts' cognitive states, this study proposes an innovative Virtual Reality (VR)-based training system. Centered on three prototypical lunar missions, the system dynamically adjusts task difficulty and machine intelligence levels based on real-time cognitive load monitoring, deliberately exposing astronauts to varying cognitive stress levels. State-of-the-art sensors continuously capture multimodal physiological data (e.g., GSR, HR, SpO_2), enabling real-time task reallocation through an adaptive system. This VR framework holistically addresses multifactorial influences on astronauts' HCC performance in complex lunar environments, establishing a closed-loop integration of physiological data acquisition, cognitive load evaluation, intelligence level modulation, and task difficulty adjustment. By advancing a novel paradigm for optimizing HCC efficiency, this work lays a critical foundation for future lunar exploration in high-demand settings.

Keywords: Lunar exploration, Human-computer collaboration (HCC), Lunar mission, Virtual reality (VR), Task reallocation, Cognitive load, Multimodal physiological data, Adaptive systems

INTRODUCTION

As lunar exploration missions continue to advance, Human-Computer Collaboration (HCC) in complex tasks is becoming increasingly critical (Xie *et al.*, 2022; Ortega *et al.*, 2021). Lunar exploration operations, encompassing surface sampling, equipment maintenance, and scientific experiments, are inherently high-risk activities that demand exceptional cognitive and operational competencies from astronauts (Lin *et al.*, 2024). Research has highlighted the challenges of managing cognitive load in such high-stakes environments (Sewell *et al.*, 2018), emphasizing the need for adaptive systems to manage workload in complex tasks (Wickens *et al.*, 2021). Despite these advancements, astronauts frequently encounter high cognitive loads during task execution, which can lead to decreased task performance and operational errors (Endsley *et al.*, 2016; Chen *et al.*, 2014). Therefore, effectively managing astronauts' cognitive load and optimizing HCC efficiency have become urgent challenges for current lunar exploration missions.

In recent years, virtual reality (VR) technology has emerged as a highly immersive simulation tool, widely used in human factors engineering research. Studies have explored VR's potential in creating realistic training environments, demonstrating its ability to simulate complex operational scenarios with high fidelity (Aylward *et al.*, 2021). Further research has emphasized VR's role in enhancing user immersion and engagement, making it an ideal platform for studying human-computer interaction (Han *et al.*, 2017). The integration of VR into human systems has been discussed, particularly in military and aerospace applications, where it has been used to improve task performance and reduce training costs (Pirker *et al.*, 2022). Additionally, VR has been highlighted as a tool for simulating high-stress environments, such as space missions, where real-world training is impractical (Finseth *et al.*, 2022). Despite these benefits, existing VR systems still face limitations in cognitive load management, including the lack of dynamic task allocation mechanisms and real-time load adjustment capabilities (ElGibreen *et al.*, 2019). This underscores the urgent need to develop an adaptive task allocation system based on VR, which has both significant research value and practical importance.

Cognitive Load Theory (CLT) provides a theoretical framework for task allocation and human-computer collaboration. CLT was introduced to understand how cognitive load affects learning and performance, categorizing it into intrinsic, extraneous, and germane loads (Schnotz *et al.*, 2007). The theory initially proposed that intrinsic load relates to task complexity, extraneous load to the task's presentation, and germane load to the learning process (Bannert *et al.*, 2002). Subsequent research has expanded this framework, demonstrating how CLT can optimize instructional design and task performance (Haji *et al.*, 2015). In lunar exploration tasks, astronauts' cognitive load primarily results from task complexity, environmental stress, and information processing demands (Nasrini *et al.*, 2020). Therefore, real-time monitoring and classification of cognitive load, combined with dynamic task allocation strategies, can effectively reduce astronauts' cognitive burden and improve task performance (Gutiérrez *et al.*, 2023). However, most of the existing research on HCC cognitive load mainly focuses on the assessment of cognitive load after the task, lacking the monitoring of cognitive load during the task and the utilization of relevant data (Longo *et al.*, 2019). Real-time cognitive load feedback is of crucial importance in critical and high-risk missions like lunar missions (Kyriaki *et al.*, 2024).

Despite progress in human-computer collaboration research, most studies have focused on controlled environments, such as cockpit and aircraft cabin settings. Research has shown that while automation can reduce workload, it can also lead to complacency and skill degradation (Endsley *et al.*, 2016). Similarly, studies on HCC in military operations have found that effective communication and task allocation are critical for mission success (Li *et al.*, 2021). However, there is a significant gap in research addressing the complexities of lunar exploration environments, where human-computer collaboration must contend with unique challenges such as low gravity, limited communication, and high-stakes decision-making. Furthermore, while VR has been used as a tool to experience unknown environments, it has not yet been fully utilized as a quantitative tool for assessing cognitive load in these complex scenarios. Recent developments have demonstrated the potential of VR-based cognitive training systems for real-time cognitive load monitoring, and the ability of VR to capture physiological data in immersive environments has also been explored (Shen *et al.*, 2021). However, these studies have not addressed the specific needs of lunar exploration tasks, underscoring the urgency of developing a robust framework for cognitive load management in these scenarios.

This study makes two significant contributions: 1) It proposes a three-level cognitive load classification system for adaptive task allocation, enabling real-time monitoring and adjustment of intelligence level based on multimodal physiological data. 2) It designs and develops a VR-based Lunar mission simulation environment, providing a high-fidelity experimental platform for cognitive load reallocation research.

SYSTEM DESIGN

Human-machine task allocation directly affects astronauts' cognitive load. A task allocation system based on real-time cognitive load data allows dynamic adjustments between humans and machines, optimizing cognitive load and enhancing performance. The machine's intelligence level is inversely related to astronaut cognitive load: as machine intelligence increases, cognitive load decreases, collectively forming different HCC modes (see Figure 1). Traditionally, machine intelligence is classified into 5 or 10 levels (Endsley *et al.*, 1987), ranging from fully human-executed tasks to fully machine-executed tasks. However, this complexity hinders system design, particularly in lunar exploration, where tasks are multifaceted. Therefore, this study simplifies the classification to three levels (see Table 1), corresponding to three levels of human cognitive load (see Table 2).

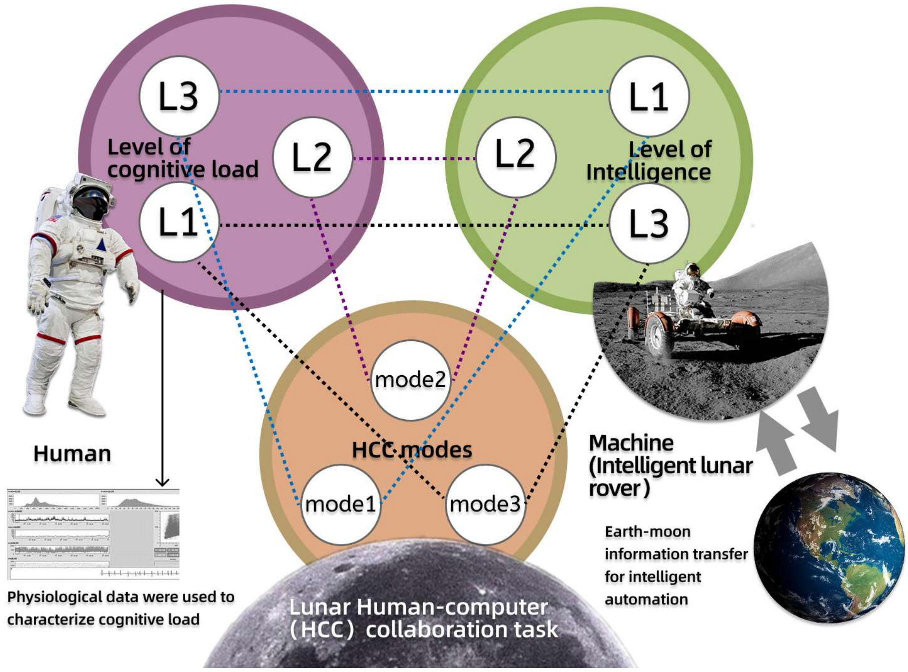


Figure 1: Cognitive load-based intelligence level adjustment model.

Table 1: Machine intelligence level settings.

Level of Intelligence	Feature
Level 1	Providing device information perception, no environmental awareness, and the machine does not perform any automated tasks.
Level 2	Provides device information perception and basic environmental awareness and analysis, but cannot execute or make decisions.
Level 3	Autonomous perception and analysis, offers operational suggestions, execute and make decisions.

Table 2: Human cognitive load level settings.

Level of Cognitive Load	Level of Intelligence	Feature
Level 1	Level 3	Human's psychological and physiological state is relaxed, and the task execution proceeds smoothly.
Level 2	Level 2	Human's cognitive load is at a moderate level; although the task can still be completed, some small errors may begin to occur.
Level 3	Level 1	Huaman's cognitive load is extremely high, task performance may be noticeably affected, and the error rate is higher.

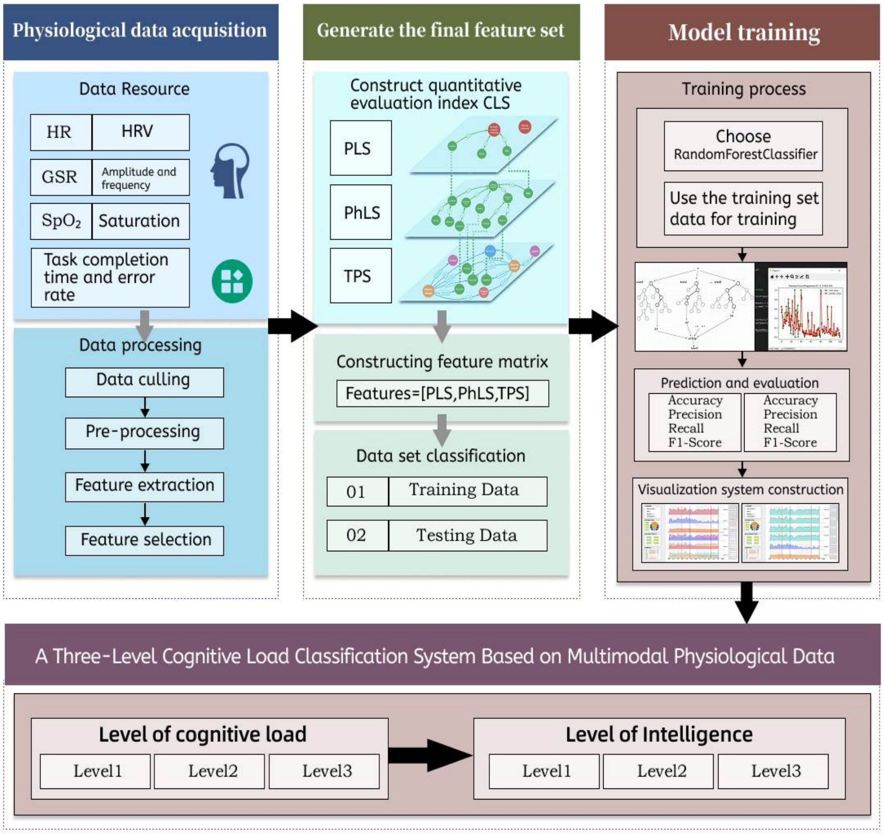


Figure 2: System construction and model training.

In terms of cognitive load classification and quantification, the study adopted a multimodal data fusion approach, combining psychological, physiological, and task execution indicators to form a comprehensive Cognitive Load Score (CLS). As shown in Figure 2, we developed a Three-Level Cognitive Load Classification System, which utilized a Random Forest Classifier trained on the ASCERTAIN dataset to classify cognitive load levels in real time. The dataset, which includes physiological signals such as GSR, HR, and SpO_2, was used in this study. The raw data was preprocessed by removing noise, normalizing the signals, and addressing any missing values. The relationship between these physiological signals and cognitive load is as follows: GSR reflects psychological load, with greater fluctuations indicating increased mental effort or stress. HR variability (SDNN, RMSSD) and SpO_2 levels were used to assess physiological load, as elevated HR and decreased SpO_2 generally indicate higher physiological strain. The Task Performance Score (TPS) was derived from task completion time and error rate, with longer completion times and higher error rates corresponding to greater cognitive load. The three key scores—PLS, PhLS, and TPS—formed the feature set:

$$Features = [PLS, PhLS, TPS]$$

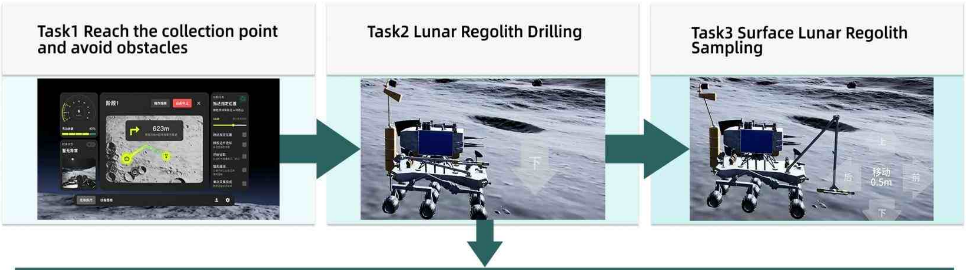
This feature set was used as input to train a Random Forest Classifier. The model's performance was evaluated using metrics such as accuracy, precision, recall, and F1 score, ensuring the accurate classification of cognitive load into three levels: Low (L1), Medium (L2), and High (L3). Finally, to facilitate real-time monitoring during subsequent training or experiments, a visualization system was developed. This system displays the real-time cognitive load status of the user by using the trained model to classify cognitive load levels, while also visualizing the physiological data (HR, GSR, SpO_2) over time. The interface provides immediate feedback on the user's cognitive load, enabling adaptive task allocation and optimizing human-computer collaboration, thus improving task performance and safety. By integrating multimodal physiological data with machine learning, this system provides an efficient solution for cognitive load classification and real-time monitoring.

METHOD

Virtual Task Design

The Virtual HCC training task design is conducted entirely using VR, with participants wearing VR headsets throughout the process. The primary means of interaction are through the use of controllers and hand gestures to control the Machine (Intelligent lunar rover). Additionally, in Task 2 and Task 3, voice interaction is incorporated to to control the lunar rover to enhance the user experience. The VR interface displays complex information, providing a comprehensive and immersive environment for task execution. This design allows for an integrated evaluation of human-machine collaboration under different levels of intelligence, utilizing advanced interactive technologies to ensure smooth task completion in lunar exploration scenarios.

Specifically, as shown in Figure 3, these tasks are not only exemplary but also thoroughly exhibit the cooperation modalities and efficiencies between humans and machines at diverse intelligence levels, all made possible within the immersive VR environment. According to a three-level cognitive load classification system, as the cognitive load (L1, L2, L3) varies, the machine's intelligence level correspondingly adjusts to match the grade. Concurrently, the tasks assigned to users under different intelligence levels are also adapted accordingly. This is to alleviate the task complexity for users under high cognitive load and reduce the cognitive burden. Task1 is reaching the collection point while circumventing obstacles. The objective is to guarantee the vehicle's smooth arrival at the lunar surface collection point and steer clear of impediments en route. Varied intelligence levels entail distinct operational approaches. In the L1 stage, where humans hold the decision-making authority, the operator manually charts the route and maneuvers the vehicle. When transitioning to the L2 stage, with the machine lending assistance to humans, the system offers cues for the nearest available route. Advancing to the L3 stage, where the machine assumes decision-making power, it autonomously plans the route and undertakes navigation. The lunar soil drilling task mandates drilling operations on the lunar surface. As the intelligence level ascends, control progressively transfers from humans to machines. At the L1 level, the operator manually governs the drilling depth and angle. By the L2 stage, the system prompts the operator to make requisite adjustments. Come the L3 stage, the system seizes full control of the drilling process, automatically calibrating the drill bit's angle and depth based on real-time data. The lunar soil surface sampling task zeroes in on sampling the lunar soil surface. Mirroring other tasks, the operation gradually transforms from manual control to automated system control. In the L1 stage, the operator dictates the commencement and conclusion of sample collection. In the L2 stage, the system proffers prompts for sampling maneuvers. Finally, in the L3 stage, the machine assumes complete responsibility for fulfilling the collection and storage procedures.



HCC task division under each intelligent level(L1，L2，L3)

operation	Machine structure	Specific task design	L1 : Human has decision-making power	L2: Machine aided human	L3 : Machine has decision-making power
Task1	vehicle wheel	Search for collection points	Check the map to find the nearest marker	The machine has no decision-making power	Prompt Route for the nearest point
		Design routine	Manual route plotting	Prompt Shortest route	Route plotting
		Proceed to the collection point	Manual control to reach the point	Navigation	Navigation
		obstacles avoidance	Manually identify rocks or lunar craters	Reminding	Avoid obstacles and give directions
Task2	auger stem	Feed down multiple times	Manual control of moving distance	Prompt (No specific operation data)	Prompt(With specific operation data)
		Multiple collection	Manually start/end a single collection	The machine has no decision-making power	Start/end a single collection
	storage compartment	storing	Manually finish the storage operation	The machine has no decision-making power	Finish the storage operation
Task3	End sampler	Feed down multiple times	Manually control the moving distance	Prompt(No specific operation data)	Prompt(With specific operation data)
		Adjust the angle of the robot arm	Manually control the rotation	Prompt(No specific operation data)	Prompt(With specific operation data)
		Sampling	Manually Start/end a single Sampling	The machine has no decision-making power	Control the start/end of a single Sampling
		Multiple collection	Manually start/end a single collection	The machine has no decision-making power	Control the start/end of a single drilling
	storeage compartment	storing	Manually finish the storage operation	The machine has no decision-making power	Finish the storage operation

Figure 3: Design of lunar surface missions based on the level of intelligence.

VR Training System Design and Development

The system is deployed on the Meta Quest 2 and developed using Unreal Engine (UE), providing an immersive virtual reality (VR) environment that supports multiple modes of user interaction, including controller-based input, gesture recognition, and voice commands. Controller-based interaction allows users to intuitively manipulate the virtual environment and perform tasks, while the gesture recognition system, which utilizes advanced hand tracking technology, enables natural, touch-free input, enhancing user engagement. Additionally, voice interaction capabilities are integrated, enabling users to issue commands or receive feedback through speech, further improving accessibility and usability.

For physiological data acquisition, the system utilizes the Neuracle multimodal data collection tool, which facilitates real-time monitoring of key physiological signals, including heart rate (HR), electrodermal activity (GSR), and blood oxygen saturation (SpO_2). These physiological signals play a pivotal role in quantifying cognitive load, allowing for continuous, real-time assessment of the user's mental and physical workload during task execution.

As shown in Figure 4, in the training scenario, one observer monitors the system to ensure accurate experimental records, while the trainee, equipped with the VR headset, sequentially performs three distinct tasks within the VR environment. The system integrates these task performances with the Three-Level Cognitive Load Classification System, leveraging real-time physiological data to evaluate and classify cognitive load into three distinct levels: low, medium, and high. Based on this classification, the system dynamically adjusts the automation level of the intelligent lunar rover, providing personalized feedback on task load. This adaptive mechanism ensures that the rover's automation is in sync with the user's cognitive state, enhancing task performance and user safety by optimizing human-machine collaboration. The continuous feedback and adjustment of cognitive load also facilitate real-time decision-making, thereby improving the overall efficacy and safety of the training process.

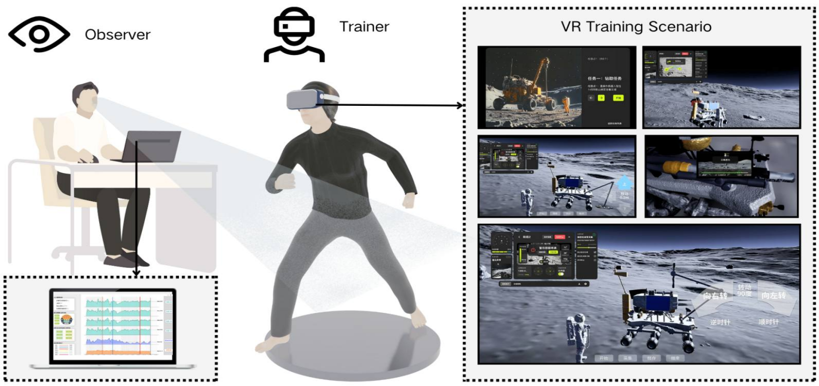


Figure 4: Specific training scenario.

CONCLUSION AND FUTUREWORK

This study has made notable progress in handling HCC challenges for lunar exploration. The three-level cognitive load classification system and

VR-based lunar task simulation environment are crucial steps towards optimizing astronaut-machine cooperation and reducing cognitive load. By combining multimodal psychological, physiological, and task performance data, we've enabled efficient task allocation between humans and machines. The VR training system offers a great platform for HCC research with task reallocation.

Looking ahead, future efforts will focus on key aspects. Firstly, we'll expand our multimodal physiological data collection. Incorporating brainwave and eye-tracking data will deepen our understanding of astronauts' cognitive states, especially during complex lunar tasks. This addition will enhance the precision of our cognitive load classification, providing more accurate support for task redistribution. Secondly, more diverse and challenging mission scenarios will be designed. From handling equipment malfunctions at lunar bases to conducting long-distance sample collections, these scenarios will better equip astronauts for the uncertainties of actual lunar exploration. This will not only test the adaptability of our HCC systems but also improve astronauts' practical skills. Most importantly, we'll conduct full-scale system validation experiments. By testing our HCC frameworks in analog space environments replicating lunar conditions, we can identify and address potential issues. This real-world verification is essential for the application of our technologies in upcoming lunar base construction and long-duration missions. We look forward to the fact that our research will play a significant part in facilitating the training of astronauts for future long-term lunar assignments.

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