A Virtual Reality Simulation Pipeline for Online Mental Workload Modeling

Robert L. Wilson¹, Daniel Browne¹, Jon Wagstaff¹, Steve McGuire¹

Abstract
Seamless human robot interaction (HRI) and cooperative human-robot (HR) teaming critically rely upon accurate and timely human mental workload (MW) models. Cognitive Load Theory (CLT) suggests representative physical environments produce representative mental processes; physical environment fidelity corresponds with improved modeling accuracy. Virtual Reality (VR) systems provide immersive environments capable of replicating complicated scenarios, particularly those associated with high-risk, high-stress scenarios. Passive biosignal modeling shows promise as a non-invasive method of MW modeling. However, VR systems rarely include multimodal psychophysiological feedback or capitalize on biosignal data for online MW modeling. Here, we develop a novel VR simulation pipeline, inspired by the NASA Multi-Attribute Task Battery II (MATB-II) task architecture, capable of synchronous collection of objective performance, subjective performance, and passive human biosignals in a simulated hazardous exploration environment. Our system design extracts and publishes biosignals through the Robot Operating System (ROS), facilitating real time psychophysiology-based MW model integration into complete end-to-end systems. A VR simulation pipeline capable of evaluating MWs online could be foundational for advancing HR systems and VR experiences by enabling these systems to adaptively alter their behaviors in response to operator MW.

Index Terms: Human Robot Interaction—Human Robot Teaming—Virtual Reality—Cognitive Load Theory Mental Workload—Psychophysiology—Biosignals—Multimodal Modeling

1 Introduction
Frameworks for Mental Workload (MW) modeling, particularly for implementation in human robot interaction (HRI) and teaming, typically operate on limited biosignals and are incapable of operating online, leaving room for vast improvements in MW model development and evaluation. Human-Robot (HR) teams, in both the physical and virtual domains, are transitioning to peer-like paradigms where each team member can dynamically respond to the current state of the other. In particular, improvements in MW for high-risk environments (e.g., driving, surgery, exploration) stand to improve safety and mission outcomes. However, data collection in these environments, a known strategy for improving model outcomes, can be risky and quite costly. Virtual Reality (VR) is a key tool for improving MW models through data collection closer to the operational environment, without the costs and risks associated with real operations.

Model mismatches between HR teammates, often due to poor MW models, can risk detrimental outcomes. Human operators function optimally within individual workload boundaries. Cognitive overload can lead to stress and operational mistakes, while cognitive underload can result in a lack of motivation or attention drift and decrease team performance. Operator interruption at inopportune times can increase cognitive demands and negatively impact mission efficacy.

Cognitive Load Theory (CLT), the preeminent model of human cognitive architecture, provides a theoretical framework for characterizing and formalizing MW. CLT suggests MW is a composite of intrinsic, extrinsic, and germane loads. Intrinsic load relates to the effort required to learn a particular concept. The section of MW related to the information presentation format defines the extrinsic load. Germane load encompasses the processing involved in understanding information relevant to the task at hand. Different component combinations indicate various levels of MW. The NASA Multi-Attribute Task Battery II (MATB-II) provides a well-studied and useful structure for manipulating MW. MATB-II consists of four main sections: Resource Management (RM), tracking, System Monitoring (SM), and communications. The difficulty of each MATB-II section can be independently altered, allowing for fine-grained experimental control. However, the use of MATB-II has been mostly relegated to traditional on-screen testing.

MW modeling predictions could improve via a robust multimodal model based on passive biosignals integrated into a VR system. Regardless of the chosen MW model (e.g., supervised learning, reinforcement learning), psychophysiological analysis aims to map a hidden cognitive state (e.g., MW) to observable external manifestations by teasing out concomitants (physical traits that map to many cognitive functions). Multimodal biosensor models are on the rise, but are rarely robust in design (i.e., include more than two biosignals), allowing for limited model performance. CLT indicates data collection and downstream model performance are likely to improve with the use of task relevant data. However, most MW work does not employ a relevant task for data collection and training, introducing a major disconnect between theory and practice. A VR environment not only enables studies with higher task relevancy, which is particularly useful for MW models aimed at high-risk scenarios, but also facilitates online model use in addition to more traditional offline evaluation.

Here, we describe an online VR environment, specifically designed to modulate MW, and the real-time data the pipeline produces. A robust sweep of biosensors allows for multimodal feature extraction. The VR framework, complete with realistic motion cues, enables deployment and possible evaluation of both closed (online) and open (offline) MW models, in task relevant settings. The VR pipeline facilitates passive biosignal generation potentially closer to those that could be elicited during the actual task, thus likely improving MW model performance, particularly in high-risk scenarios.

2 Relevant Background
We constructed our VR model by combining multiple aspects of research in both HRI and psychology into a multifaceted...
Figure 1: Our lunar rover VR simulation produces online time synced human performance and in-simulation objective measures for investigation of online mental workload estimation. The exploratory simulation, founded on MATB-II, allows for manipulation of each component separately. All four control components play a role in a MW model (i.e., Intrinsic, Extrinsic, Germane Load). A biosensor suite records a robust sweep of raw physiological data and extracts relevant biofeatures data during play (see subsection 4.3). In-game objective data and extracted biofeatures are time synced through ROS. Between-run TLX survey results paired to time synced biofeatures and objective measures enable MW modeling online and post simulation.

2.1 Performance Measures

Performance measures display an intricate relationship to MW [14]. Optimum MWs consistently yield maximized objective performance [18, 45]. In VR, objective performance measures have demonstrated improved task performance and been linked to MW [6, 44]. A multitude of methods have been subjective surveys explored in relation to MW [39]. The NASA Task Load Index (NASA-TLX) survey has demonstrated a relationship to MW in a variety of modalities [17], including proving the usefulness of VR in modulating MW [13, 27].

2.2 Biosignals

Physiological signals give quantitative insight into an individual MW [11]. For our work, we selected six raw biosignals (and multiple derived features) that have demonstrated MW correlations: Electrocardiogram (ECG), Electrodermal Activity (EDA), Photoplethysmography (PPG), Respiration, Skin Temperature (ST), and Pupillometry.

ECG, derived from cardiac electrical activity, and PPG, blood flow interpolation via light refraction, provide indirect insight into MW via cardiovascular activity measurement [11]. Temporally, ECG measures (HR and Heart Rate Variability (HRV)) have demonstrated relationships to MW [11, 38, 45]. In the frequency domain, power bands increase or decrease as a function of task load [11]. PPG, either individually or in conjunction with ECG, may provide more useful MW estimates [26]. For example, calculating Stress-Induced Vascular Response Index (sVRI), a PPG signal derivative, requires a lower time period of analysis to estimate MW than HRV, making it a good candidate for real-time estimation [48]. Notably, physical exertion confounds cardiovascular measures, making them poorly suited for tasks with significant physical loads [15].

Dermal measures relate to MW as a response to general ANS stimulation. EDA, also known as Galvanic Skin Response (GSR), quantifies the electrical resistance of skin. EDA waveforms consist of tonic, slow acting, and phasic, event specific, responses [9]. Tonic components have indicated moderate utility for MW estimation (e.g., tonic components loosely correlate with MW), while shorter, more frequent, phasic peaks suggest a stronger MW relationship [9]. ST can be utilized in MW estimations, but with temporal limitations of slow rise times and delayed event responses. Generally, ST decreases in response to MW [28]. However, ST responses to MW may be location dependent [1].

The Respiration Waveform gives insight into MW through breathing rate and variations [15]. In a relaxed state, a human breathes slowly and consistently. However, as MW rises, overall breathing rate increases along with an increased prevalence of irregular rhythms, quick variations, and cessations [26].

Pupillometry measures fluctuations in pupil size and reactivity, which have a direct relationship to MW through the CNS [32]. For example, variations in the rate and magnitude of microsaccades, involuntary eye movements that occur during fixation, can separate different MW levels [27]. One study specifically records pupillometry in VR and found a positive correlation between pupil diameter and subjective task load scores [41].
2.3 VR in MW modeling
VR provides an immersive environment capable of simulating complex situations in a controlled manner [10]. While VR has been employed in a variety of use cases [24, 30], the utility of VR starts to shine in high-risk scenarios. Driving simulations commonly vary route options or obstacle difficulty in order to induce different MWs [2, 21, 47]. Users of surgical simulators have subjectively reported the utility of VR in operations preparation [7] and objectively demonstrated decreased MWs after system use [49]. The use of VR for flight simulation assessment has been able to differentiate between low and high MWs [4, 23].

3 System Design
Motivated by the cognitive state insights provided by performance and biosignal measures as well as the role VR can play (see section 2), we designed a VR exploration environment with the aim of modulating MW through simulation difficulty. While playing the simulation, the user dons three biosensors (i.e., Zephyr Bioharness, Empatica E4, HTC Vive Pro Eye). The system collects objective performance and physiological measures online, with NASA-TLX survey responses collected between runs (see Figure 1). The Zephyr Bioharness communicates directly with Robot Operating System (ROS) while the Empatica E4 and Unity connect to ROS through Windows via the vendor provided streaming server and rosbridge respectively. ROS time synchronizes all collected data, which can be used in a variety of MW models, enabling real-time (closed loop) use while still providing traditional offline (open loop) analysis.

The simulation begins with the user randomly placed on a 1 km² lunar texture, onboard the Apollo rover. A prompt informs the user of the mission scenario and objective. While on an exploration mission to an area of scientific interest (i.e., objective point), the rover’s autonomous systems have failed. The rover’s responsibilities now fall on the human as the user navigates to the objective point.

3.1 Simulation Design
The simulation tasks the user with navigating to a randomly generated objective point (represented as a green column [Figure 2A]) and drop a marker while aboard the Apollo lunar rover, in the shortest amount of time. A 6-axis motion platform provides motion cues (Figure 1), generated by the lunar texture the user drives across, complete with corresponding lunar physics (e.g., gravity of 0.166G). A side mounted Hands On Throttle And Stick (HOTAS), in the same layout as the in simulation rover, provides in game movement and interaction (Figure 1). While navigating, the user must track or respond to various rover alerts, all chosen in relationship to the MATB-II due to its ability to regulate the various components of MW. Upon objective completion, a NASA-TLX prompt appears.

3.1.1 Tracking
A radar indicator (Figure 2B) details the signal strength and optimal direction of the on-board radar dish. The user must maintain optimal connection to the stationary relay station as they navigate through a button on the HOTAS stick. The user’s field of view includes the actual on-board radar for added visual feedback. As signal strength worsens, the radar indicator drops bars and changes colors (i.e., green to yellow to red), while the arrow indicates the necessary directional change. If the user does not correct a drop in signal strength, the indicator will start flashing and increase flashing frequency over time.

3.1.2 Communication
While navigating, contact must be maintained with either the base station or the lunar habitat. Separate audio (i.e., male for base station and female for lunar habitat) and visual (Figure 2C) prompts tell the user which frequency to broadcast to. Upon receiving the prompt, the user must switch...
channels via a button located on the HOTAS stick. Delays in response cause the prompt to reoccur at an increased frequency. The system may also separately ask the user to report in, prompting a separate trigger response.

3.1.3 Resource Management

Distance traveled as well as motor speed and temperature dictate the rover’s limited battery, part of the RM triad (Figure 2D). Overdrive capabilities, shown in the on-board display (Figure 2E), can increase speed for a short burst but at the cost of significant battery life. Depletion of rover battery results in a failed run. CO₂ management, which requires the user to expel its contents after reaching a certain threshold, and O₂ consumption, the depletion of which results in a failed run, act as the other two constituents. Breathing rate, supplied by the Zephyr Bioharness, drives both CO₂ buildup and O₂ consumption, but at different scales (i.e., CO₂ buildup happens multiple times a run while O₂ depletion is a one time event).

3.1.4 System Monitoring

Motor temperature and rover speed fulfill the role of SM (Figure 2C). The on-board display reflects rover temperature variations, which are controlled by the HOTAS throttle on the motion platform. Throttle speed and terrain dictate the actual rover speed, with the user feeling all motion in real time through the motion platform. Vehicle torque drives motor temperature. If motor temperature reaches a critical temperature, the entire rover will stall while the system cools down, drastically affecting completion time. An overdrive button increases the torque over the recommended limit for a short time at the cost of an increased motor temperature.

3.2 Trial Design

We structured each run in a repeated measures fashion, designed to last for one-hour (Figure 3). Each trial begins by equipping the user with biosensors and initializing the ROS data collection. Upon situating themselves in the motion platform and being briefed on the mission objective, the user explores the lunar terrain in free play mode, with the Heads Up Display (HUD) and on-board display turned off, for five minutes. The five-minute period acts as an establishment of physiological baseline [18]. Afterward, the system sets the run’s in-game difficulty, an objective point appears, and the information systems (i.e., the HUD and on-board display) turn on. The user then completes the task as previously described (see subsection 3.1). After a run completion, the user enters three minutes of free play to reestablish baseline physiology. Subsequently, the system varies run difficulty (i.e., low to high or high to low) and begins the cycle again. The user completes four separate runs (two high and two low difficulty) during testing.

4 System Output

ROS time syncs all collected data across multiple sensors and operating systems (i.e., Linux and Windows). After an individual study completion, a single rosbag carries all data for a single run. The ROS architecture enables isolation of each data stream to separate topics, with each topic handling different measurement types (e.g., ECG topic, rover topic, NASA-TLX survey topic). The system collects in-game objective performance measures, between run NASA-TLX surveys, and multiple biosignal (e.g., EDA, Pupillometry) features.

4.1 Objective Measures

In-simulation measures indicate user performance. For the rover, the system reports rover pose (position, rotation), twist (velocity, angular velocity), fuel, and motor temperature at 10 Hz. Boolean flags mark radio requests and responses. Twelve total states represent antenna accuracy. We also collect current CO₂ and O₂ (at 10 Hz), the current trial leg and difficulty (see subsection 3.2), and elapsed time of play.

4.2 Subjective Measures

A NASA-TLX survey appears after the user has reached the objective and dropped their marker. The survey asks questions aimed at subjectively evaluating user performance (e.g., How mentally demanding was the task?), in six categories: mental demand, physical demand, temporal demand, performance, effort, and frustration.

4.3 Biofeatures

4.3.1 Raw Biosignals

Raw biosignals are collected at resolutions specified by the manufacturer. Using the vendor supplied Windows streaming server, the Empatica E4 collects and relays raw PPG at 64 Hz as well as EDA and ST at 4 Hz. The Zephyr Bioharness directly relays a raw respiration waveform at 1.008 Hz and ECG waveform at 252 Hz. Pupillometry, provided through the HTC Vive Pro Eye linked to Unity, reports 2-D eye position and pupil diameter at 120Hz.

4.3.2 Derived Biosignal Features

Using third-party packages [38], our system derives biosignal features with a 30s windowing interval [18][33]. Biofeatures are derived in both time and frequency domains, ranging from traditional features (e.g., heart rate) to newer approaches (e.g., smooth pursuits). A full list of derived biosignal features can be found in Table 1.
5 Discussion

MW models are critical for effective HR teaming and immersive VR experiences, but available processes rarely include online capabilities or relevant settings. This work developed a VR pipeline capable of time synchronizing numerous objective and subjective performance data with passive biosignals, which can be utilized in MW modeling on or offline (Figure 1). VR task design compels users to focus on the four pillars of MATB-II (i.e., tracking, RM, SM, and communication) while navigating to an objective (Figure 2). VR enables situational data collection, by emulating high-risk extraplanetary exploration. Raw biosignal data (Figure 4) empowers our pipeline to extract a plethora of relevant biofeatures (Table 1), close to real time, providing a relevant test bed for open and closed loop MW model exploration.

The immersive capability of VR, coupled with synchronized biofeatures, enable a deep exploration of MW modeling. Immersive environments ensure realistic data collection by causing more realistic mental and physical responses [12]. A multitude of biofeatures relate to MW (see subsection 2.2), yet few studies directly compare information gain across modalities [45]. Direct comparisons could inform systems designed for resource constrained environments. machine learning (ML) model approaches are end goal dependent (e.g., training evaluation or HRI). Online methods, such as deep learning (DL) or reinforcement learning (RL) models, may improve HR teaming efficacy and safety [25, 29]. Offline modeling, such as traditional supervised learning models, may be more appropriate for testing individual skill sets [33]. The flexibility of our pipeline design with ROS integration allows this approach to be ported to a plethora of VR environments, or even into physical robotic systems.

We learned many lessons and discovered implicit design limitations while executing our system design. Many technical issues stemmed from communicating and synchronizing across two different operating systems (i.e., Windows and Linux). The latest iteration of ROS, ROS2, is available for Windows. However, keeping our system in Linux enables downstream use in real-world robotic systems, the majority of which operate on Linux. The Empatica streaming server instability and hardware limitations (e.g., dropping or not discovering devices and specific Bluetooth module requirements) was an unforeseen complication, which could have been remedied with an open-source option; we are currently developing such an option for community benefit. Poor error messaging made debugging the ROS to Unity connection difficult (e.g., mistyped Unity components break the connection but do not indicate where the error occurred).
Incompatibilities between Unity VR and Steam VR hindered full headset integration, prompting a switch to Unity XR. We tested many iterations in order to balance the MATB-II style features to ensure playability and goal completion while being able to modulate difficulty. Our Object Oriented Programming (OOP) approach for feature extraction allows easy third-party package changes, ensuring easy future modifications. Other biosensors could be added to the suite (e.g., Electroencephalography (EEG), Electromyography (EMG)), but may be impractical for VR or result in large rosbag or rosmsg files that can slow down system processing. The 30s windowing time temporally limits MW predictions. Shortening the window time without significant information loss may be possible [43].

Simulation design leaves the door open for a variety of future work. An independent samples t-test would validate simulation difficulty against MW (i.e., over or under-loaded). We have begun human subject data collection to this end ($\alpha=0.05$, $\beta=0.8$ | $n\approx35$). With a subject database, we can explore a variety of MW ML models. We intend to evaluate traditional multivariate linear and simple supervised learning approaches, followed by DL and RL methods. To utilize the MW models online, we are developing an artificially intelligent (AI) agent equipped with the MW model and capable of online simulation control variation.

6 Conclusion

MWs could be useful in a wide variety of systems, from HRI and teaming to operator training and testing. Such systems would utilize ML-based MW models that ideally function on passive biosignals produced in realistic environments. VRs immersive capabilities facilitate reproducible simulations of complex scenarios, fulfilling this critical need. The developed simulation, based on CLT and MATB-II, aims to achieve this goal in conjunction with a robust sweep of biosignals and features. The online time synced design not only allows for offline and open loop analysis, but enables real-time MW assessment, which stands to improve a variety of MW models and form the basis for closed-loop control systems reactive to an operator’s MW.

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