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# Measuring Mental Workload and Brain Dynamics in Prosthesis Motor Learning over Multi-Session Practice

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*We pledge on our honor that we have not given or received any unauthorized assistance on this assignment.*

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# Introduction

The capability of humans to adapt their motor behavior and learn new motor skills is critical to interact with their changing environment as well as for integration with new machine interfaces, such as assistive technology (Casadio, Ranganathan, & Mussa-Ivaldia, 2012; Kitago & Krakauer, 2013; Mussa-Ivaldi et al., 2011). Such learning capability depends on the recruitment of cognitive-motor resources (Wickens, 2002). Mental workload (MWL), which is an important component in understanding learning, can be defined as the relationship between the deployment of neural resources and imposed task demands (Sharples & Megaw, 2005; Young et al., 2015). Although a large body of work has examined the behavior and cortical dynamics underlying the motor learning processes, most of this prior effort generally did not examine changes in mental workload through multiple practice sessions and did not consider individuals with upper limb (UL) loss (Marchand, de Graaf, & Jarrassé, 2021; Park & Zahabi, 2022).

In this work, UL amputees were approximated by considering healthy individuals using bypass prostheses (Bloomer, Wang, & Kontson, 2018; Wang et al., 2021). Based on the work by Bloomer and Wang, able-bodied individuals can serve as a reasonable proxy for amputees while using these bypass prostheses. From a methodological standpoint, the use of human-body interfaces such as a bypass prosthesis is interesting since it requires participants to acquire a novel and unusual sensorimotor mapping, mitigating the influence of prior motor experiences and ultimately offering a fairly unbiased learning paradigm (Casadio, Ranganathan, & Mussa-Ivaldia, 2012; Mussa-Ivaldi et al., 2011). Thus, we employed this approach here, along with electroencephalography (EEG), which was used to assess the cortical dynamics as participants completed the learning task in order to objectively assess mental workload. In addition, surveys were employed to subjectively assess the level of workload perceived by the participants along with performance (e.g., time, smoothness, number of blocks transported within a fixed time period) collected via an inertial measuring unit.

Overall, the aim of this research was to examine the concomitant changes in performance (e.g., number of blocks transported within a fixed time period) and in mental workload (by means of surveys and the cortical dynamics indexed by EEG) that occur when healthy individuals learn to operate a bypass prosthetic device via multi-session practice to perform a variety of motor tasks of daily living. This work can inform not only the human cognitive-motor processes underlying mental workload and performance during learning but also, to some degree, the rehabilitation/training of UL amputees, as well as the design and evaluation of prosthetic devices.

# Chapter 1: Literature Review

Existing research generally examines human motor learning, mental workload, and rehabilitation of UL amputee populations separately, not necessarily combining behavioral performance and cortical dynamics. Since the present research will encompass the notions of mental workload and motor learning in a context where individuals operate UL prostheses, the corresponding available literature will be reviewed to inform our research design and direction. This literature review is divided into four sections. First, the concept of mental workload and measurements will be introduced. A second section will briefly review the current literature related to mental workload in a performance context in both healthy and amputee populations. The third section will introduce the notion of motor learning. The fourth and final section will provide a brief review of the current literature related to mental workload in a motor learning context considering healthy and amputee populations. Each section serves as a brief report of what has already been accomplished in the related field and which ultimately has determined our research aims and hypotheses that are presented at the end of this chapter.

## 1.1 Mental Workload

### 1.1.1 Theory

MWL considers the user experience of a given task demand, or the nature and quantity of the work performed by the user (Charles & Nixon, 2019). MWL may vary between users for the same task demand due to factors including time constraints, environment, and experience. It may also vary for the same user at different times (Sharples & Megaw, 2015; Wickens, 2002). Despite a relation between MWL and task demand, MWL is not an inherent function of task demand and thus its variation is not always proportional to task demand (Colle & Reid, 1998). Rather, MWL emerges from the interplay between the basic requirements of a task, the circumstances under which the task is performed, and the skills, behavior, attitudes, and perceptions of the user (Hart & Staveland, 1988). As a given task becomes less cognitively demanding, MWL is expected to decrease.

MWL can be divided into three cognitive loads, each related to element interactivity: intrinsic, germane, and extraneous (Sweller, 2010). Elements can be defined as anything that needs to be or has been learned, such as a concept or a procedure. Intrinsic cognitive load is the natural complexity of information to be understood, independent of the method that is used to teach the material (Sweller, 2010). It can only be altered by the act of learning or by task modification. The level of intrinsic cognitive load is assumed to be determined by the level of element interactivity. Germane cognitive load focuses solely on learner characteristics and is a function of the working memory resources devoted to the interacting elements determining intrinsic cognitive load. Extraneous cognitive load is defined as the imposition of nonoptimal instructional procedures, or information that is unrelated to the task at hand. Cognitive load is extraneous if element interactivity can be reduced without altering what is learned. Conversely, if element interactivity only can be adjusted by altering what is learned, the load is intrinsic (Sweller, 2010).

Another theory that explores the MWL associated with task performance is the multiple resource theory. This model assesses and makes predictions about a participant's ability to perform in high workload environments that require the performance of multiple tasks demanding a number of resources (Wickens, 2002). A resource, in this case, refers to an allocatable and limited capacity for perceptual and cognitive activities that falls under one or more of the four established dimensions: processing stages, perceptual modalities, visual channels, and processing codes. In such a context, MWL can be also defined as the relationship between the deployment of resources to face task demands (Young et al., 2015). The framework behind these dimensions includes perceptive, cognitive, and responsive processing stages; visual and auditory perceptual modalities; focal and ambient visual channels; spatial and verbal processing codes; and manual, spatial, verbal, and vocal responses to the presented task. Each dimension can be associated with a physiological mechanism and structure within the brain (Wickens, 2002). Using the dimensions as means to calibrate measures of resource allocation and workload, the theory demonstrates that high performance interference occurs with 1) different tasks which demand greater allocation of one or more resources and with 2) similar tasks that demand the same resources within the same dimensions (Wickens, 2002).

There are also theories relating the level of user learning and the method of learning. One theory describes the goal-free effect, in which the performance does not have an end goal, for example, asking a participant to freely use a prosthetic limb rather than asking them to accomplish pre-determined tasks with the prosthesis. The theory posits that users learn less from solving conventional problems that are required of them (Sweller, 2010). Solving any problem simultaneously requires a user to consider the current problem state, the goal state, differences between the two states, problem-solving operators that can be used to reduce those differences, and any subgoals that have been established (means-end strategy). Goal-free problems significantly decrease the number of interacting elements. Another theory, the self-explanation effect, describes how working memory resources efficiently focus on the interacting elements associated with intrinsic cognitive load rather than extraneous elements when the user is asked to explain a concept or procedure. This increases germane cognitive load because working memory resources devoted to intrinsic cognitive load are maximized.

### 1.1.2 Measurement

The NASA Task Load Index (NASA-TLX) is a commonly used survey-based measurement tool that is able to articulate and generalize workload scaling with a number of related standardized variables, all of which are derived from task-related, subject-related, and performance-related subscales (Hart & Staveland, 1988). Narrowing down a wide range of subscale possibilities, it was observed that measuring mental demands, physical demands, temporal demands, frustration, and effort provided the most significant information about workload (Hart, 2006; Hart & Staveland, 1988). The NASA-TLX model is based on the understanding that by considering the mentioned variables, especially in combination with each other, researchers will accurately reflect the MWL that an operator experiences whilst carrying out a task on a scale that is generalizable and consistent enough to allow for accurate comparison of perceived MWL across a group of operators (Hart, 2006).

There are numerous physiological measures that can be used to assess MWL as well, including electrocardiac activity, blood pressure, respiration rate, skin conductance, ocular measurements, and brain activity (Charles & Nixon, 2019). Their validity depends on the task type and the question being asked. For this study, in order to assess MWL, brain activity will be measured using EEG. EEG is often preferred by researchers in a variety of settings due to its high sensitivity, unobtrusiveness, ability to measure continuously, and relatively low cost (Gevins & Smith, 2003).

EEG serves as a reliable measure of MWL. EEG uses the flow of dendritic signals in the cerebral cortex to measure electrical activity in the human brain via conducting electrodes that are attached to the scalp at defined locations. Electrodes are connected to high-impedance amplifiers whose signals run through high- and low-frequency filters that are then sent to the electroencephalographer (Rippon, 2006). A popular technique when analyzing EEG responses is averaging, or combining, the responses created from repeating stimuli. These averaged responses are assumed to create more consistent responses by eliminating random background activity. When using this method, the results are called potentials (Rippon, 2006).

EEG analysis can describe in detail the received signal's characteristics and how they are distributed across the brain. The activity measured by EEG is described in terms of different frequencies. While frequencies are analyzed using spectral analysis, fast Fourier transform (FFT) is used to analyze the amplitude of different frequencies within the EEG signal. A widely studied frequency measured by EEG signals is the alpha rhythm, and it is read at 8-13 Hz. FFT is used to identify the alpha rhythm along with slow delta waves (<4Hz), theta waves (4-7Hz), beta waves (14-30 Hz) and gamma waves (30-50Hz). Frequency categories can be further divided into subcategories such as low and high alpha, or beta 1, beta 2, and beta 3. In the context of a MWL study, theta and alpha frequencies are of primary interest. Namely, theta variations are associated with memory, attention, action monitoring and task performance success. Alpha activity is linked to cortical activity which, based on a particular region, can involve the specific corresponding cognitive-motor processes including memory, attentional control, and sensorimotor integration (e.g., Gevins & Smith, 2003; Rietschel et al., 2012; Shaw et al., 2018). It must be noted that the alpha band can be divided into low-alpha (8-10Hz) and high-alpha (11-13Hz) components which represent cortical activity related to general arousal and task-specific processes, respectively (for a review see Hatfield et al., 2020). Beta activity is linked with specific task demands and is less widespread than alpha activity. Gamma activity is generally associated with perception and response to perception (Rippon, 2006).

MWL can be accurately assessed by combining quantifiable measures of brain dynamics with subjective surveys. EEG was selected over other biosignal-based metrics of MWL because it is highly sensitive to alertness and attention and less susceptible to changes in the environment (Gevins & Smith, 2003). It also captures brain dynamics in real-time, allowing them to be studied concurrently with motor performance. The NASA-TLX was chosen because it accounts for individual differences using a weighting scheme, which produces increased sensitivity and decreased between-rater variability (Hart, 2006). It also uses a human-centered definition of workload, rather than a task-centered definition, consistent with the idea that MWL is not inherent to the task (Hart & Staveland, 1988). Used together, the objective biosignal-based metric, EEG, and the subjective survey-based metric, the NASA-TLX, provide a more complete view of MWL changes over time and present the opportunity to probe whether participants' own MWL ratings align with the physiological signs of MWL.

## 1.2 Mental Workload in a Performance Context

### 1.2.1 Healthy population

Previous research has examined changes in MWL for various task demands for healthy populations. Many studies examining MWL in a performance context reveal that as task demand increases, the deployment of neural resources increases which results in a greater level of MWL (e.g., Gevins et al., 1997; Miller et al., 2011; Rietschel et al., 2012; Shaw et al., 2018; Young et al., 2015). More specifically, by employing spectral EEG analysis and surveys, such as the NASA-TLX, it has been demonstrated that more difficult tasks increase recruitment of attention, working memory, action monitoring and sensorimotor integration as indicated by an elevation of theta power, a decreased low/high-alpha power, an increased perceived effort and difficulty, and a decrease in or a maintenance of performance (e.g., Gevins & Smith, 2003; Rietschel et al., 2012; Shaw et al., 2018).

For instance, Shaw et al. (2018) studied the behavioral performance, NASA-TLX, and EEG data of participants completing a cognitive task under two levels of difficulty (easy and hard) and two different performance conditions (seated and walking). The results revealed that theta power was significantly higher under the walking condition compared to the seated condition, both low and high alpha powers were lower under the hard level of difficulty compared to the easy level, and the perceived effort and difficulty of the task under the hard and walking conditions relative to the easy and seated conditions increased (Shaw et al., 2018). No significant changes were observed for two measures of performance (hit rate and error rate), while some decreased performance (response time) was observed under the hard level of difficulty relative to the easy level (Shaw et al., 2018). The psychomotor efficiency hypothesis can be used to describe brain activity in relation to MWL and performance. It suggests that superior performance is associated with efficient cerebral cortical activity reflecting a low level of MWL (for a review see Hatfield, 2018).

### 1.2.2 Individuals with limb loss

While many studies have investigated changes in MWL and performance for healthy populations under varying conditions of task demand, some work has also been done to study these changes for prosthesis users. However, this area of research is more limited. Much of the research employing EEG analysis in their methodology focuses on lower limb loss as opposed to upper limb loss. Namely, several studies which examined the changes of MWL during dual-task walking in individuals with lower limb loss revealed that an elevation in task demands resulted in an elevation of the recruitment of cognitive-motor resources (as indexed by cortical activity) which was generally more prominent in amputees, particularly in individuals with more extreme amputations where the neuromechanical system was more compromised (e.g. Pruziner et al., 2019; Shaw et al., 2018). For instance, Shaw and colleagues revealed that as dual-task walking demands increased, transfemoral amputees deployed greater cognitive-motor resources compared to those with transtibial amputation along with lower or maintained performance (Shaw et al., 2019).

While several studies have examined MWL when operating lower limb prostheses, a much more limited body of work has examined concomitantly the changes of MWL and performance in a UL prosthesis (Deeny et al., 2014; for a review see Marchand de Graaf, & Jarrassé, 2021; Park & Zahabi, 2022). For instance, Deeny and colleagues required participants to complete both direct myoelectric control and pattern recognition myoelectric control of a virtual arm to explore correlations between EEG data, survey data, and performance (Deeny et al., 2014). However, when investigating brain dynamics, this research focuses solely on event related potentials, the evoked potentials caused by sensory processes that are associated with cognitive processes. Despite the virtual environment, the study identifies significant correlations. An inverse relationship between task complexity and ERP amplitudes in the EEG data was found, while self-report data was correlated with performance as opposed to cortical activation (Deeny et al., 2014). Currently, most work that focuses on upper limb loss is more performance-based in approach. Much of the existing methodology to assess performance and user experience with upper limb prostheses often disregards sensation scoring components in favor of performance-based outcomes (for a review see Diment, Thompson, & Bergmann, 2017; Wang et al., 2018). As a result, the impact of sensory experience on performance and functional ability cannot be fully appraised. Quality of motion is scored subjectively and inconsistently based on the perceived correctness and independence of movement (Wang et al., 2018). These behavioral indicators are not as comprehensive and objective as EEG, and cannot provide much insight into MWL.

## 1.3 Motor Learning

Motor learning describes the process of acquiring a new motor skill. An understanding of this process is important to understand the rehabilitation process. There are many factors that influence motor learning, including how certain motor skills are acquired, how learned skills are performed, and how these skills can be transferred.

### 1.3.1 Practice, learning, acquisition and retention

The acquisition of skills required to complete a task is foundational for future completion of the task. It is generally agreed that random order practice yields high returns for future performance as compared to constant block-order practice (Kantak & Winstein, 2012; Kitago & Krakauer, 2013). The explanation for this is related to the concept of motor memory. Previous work has focused on the motor memory processes of encoding, consolidation, and retrieval, in addition to the role of attentional resources in motor learning.

With respect to the encoding process of motor memory, Kantak and Winstein (2012) weigh two possible explanations for the contextual interference effect. Contextual interference is a concept important for creating tasks and building practice schedules as it refers to skill retention resulting from interference or random ordering in task training (Kantak & Winstein, 2012; Kitago & Krakauer, 2013). The positive results from random-order practice may be due to the subject's opportunity to create inter-task comparisons, or because the subject must reconstruct an action plan with each new task, causing a variety of skills to be fully encoded (Kantak & Winstein, 2012).

The motor memory processes of consolidation and retrieval are also explored, but are less relevant to the acquisition period of motor learning.

Retention is the process that follows acquisition. During this phase, the memory process of consolidation works to entrench the learned motor skill in the memory. Consolidation does not involve active learning, and in fact may be related to sleep (Kantak & Winstein, 2012). The effect of consolidation may be seen in improvement between subsequent sessions without much practice in the interval. Retention may be tested by asking the individual to perform the same learned task under the same conditions under which it was learned. Another type of test, called a transfer test, asks the individual to perform a related task or a variation of the learned task. Thus, while retention tests seek to evaluate how firmly the memory of a motor skill has been established, transfer tests seek to understand an individual's readiness to add new tasks and to apply a learned task to various contexts (Kantak & Winstein, 2012).

Changes in the level of performance of a task over time can reveal information about skill acquisition and retention. Kantak and Winstein (2012) note that learning is distinct from performance, or observed behavior. Performance can be influenced by a diverse array of factors, such as motivation or attention, and may not always reflect the extent to which a task has been learned. For example, a subject may not perform to their highest ability when lacking sufficient motivation. The converse may also occur; a subject may be able to perform an assigned task during a training session, but the ability to retain and replicate the movement—to truly learn it—may take more time to develop (Kantak & Winstein, 2012). It should be noted that training procedures that result in enhanced immediate performance are not as beneficial for long-term retention (Kantak & Winstein, 2012).

### 1.3.2 Attention and learning

The relationship between motor learning and attention has been well studied. In particular, it has been well established that as individuals learn and performance becomes more automatic, the engagement of attentional processes decreases (Fitts & Posner, 1967). In the context of MWL, for which attention is a primary resource, it was suggested that for skill acquisition studied using a dual-task paradigm, motor performance suffers when a secondary task is imposed on a subject in the middle of an initial task, and divided attention negatively affects motor memory when a subject is asked to perform just one task after dual-task training (Song, 2019). Kanfer and Ackerman (1989) discuss skill acquisition as a process divided into phases of declarative knowledge (initial exposure to task), knowledge compilation (continued practice), and procedural knowledge (automatic performance), and note how a subject's need for attentional resources decreases as they move through the three phases. Attention is a limited resource, and the way in which it is allocated by a subject greatly impacts the level of performance relative to their phase of acquisition. This limited supply translates into task classifications of being either resource-dependent when varying levels of attention results in varying levels of performance, or resource-insensitive when changes in attention are accompanied by minimal changes in performance (Kanfer & Ackerman, 1989). These classifications can inform the interpretation of a subject's performance and identification of relationships affected by task alteration.

In fact, increased difficulty in the process of learning may benefit retention. For example, division of attentional resources was found to be beneficial to retention when the secondary task was similar to the motor skill being learned (Song, 2019). Retention and performance can also be enhanced by focusing attention externally—that is, by focusing on the intended movement or motor skill, rather than on the movements of one's body. This allows the automatic control system to function unhindered, without the individual attempting to consciously control each movement, allowing for unconscious reflexes to aid in movement (Song, 2019).

## 1.4 Mental Workload in a Learning Context

Although MWL has been widely studied in a performance context, the examination of this concept during motor learning is more limited. In order to engage with and learn a task, an individual must utilize a set amount of cognitive and motor resources. The extent to which an individual's cognitive resources are utilized to complete a task is called MWL. In the context of learning, MWL has been found to negatively correlate with performance. From a theoretical standpoint, it has been suggested that as an individual learns, their ability to perform a task becomes automated, thereby allowing for a reduced need for the use of cognitive resources to accomplish the same level of performance (Wickens, 2008; Young et al., 2015). Several motor learning studies revealed that as individuals practice, performance improves along with a decrease in MWL that was characterized by an increase of theta and/or alpha power (e.g., Gentili et al., 2011; Gevins et al., 1997; Jaquess et al., 2018). For instance, motor performance gradually improves, and MWL decreases over practice sessions in a motor learning task employing a head control device where individuals had to learn a new sensorimotor mapping through a human-machine. It must be noted that performance changed at a faster rate than and prior to the corresponding decrease in MWL (Shuggi et al., 2019). Likewise, in an EEG study where individuals were placed in a flight simulator and learned with differing demands on each of four practice sessions, their performance improved along with an attenuation of MWL (performance improved faster than MWL) (Jaquess et al., 2018). It must be noted that the limited effort that focuses on examination of MWL during learning has two main limitations. The first is that few considered multiple practice sessions (e.g., Jaquess et al., 2018; Kerick, Douglass, & Hatfield, 2004; Shewokis et al., 2013; 2015; Shuggi et al., 2019) and, to our knowledge, none have considered prosthesis learning.

The aforementioned investigations on the relationship between MWL and performance have all involved healthy participants. As mentioned above, although interesting, these studies did not consider the changes in performance and MWL over multiple sessions while learning to operate prosthesis devices with more real-life scenarios where the demands of varying tasks are broader and more variable. Such an effort would be highly relevant to amputees who must learn to use prostheses. As such, understanding how brain dynamics and MWL correlate with performance in amputees and individuals training with prosthesis is of utmost importance. In order to circumvent the small sample populations of upper limb amputees, healthy participants are often recruited and trained on bypass prostheses to simulate an amputee learning to use a prosthesis (Bouwsema, van der Sluis, & Bongers, 2008). It must be noted that a prosthesis can be considered a human-machine interface imposing a novel and unusual sensorimotor mapping that individuals have to learn how to operate (Casadio, Ranganathan, & Mussa-Ivaldi, 2012; Mussa-Ivalidi et al., 2011). While there has been substantial research on optimizing upper-limb prosthesis training by studying performance with bypass prostheses in healthy participants (Bloomer, Wang, & Kontson, 2018), little to no research has been conducted on MWL in this context (for a review see Marchand, de Graaf, & Jarrassé, 2021; Park & Zahabi, 2022).

Many studies have also examined prosthesis training procedures but are limited in application based on a purely behavioral approach (e.g., Bloomer, Wang, & Kontson, 2020; Huinink et al., 2016). For instance, Huinink and colleagues (2016) assessed bypass body-powered prosthesis users as they performed various tasks over multiple sessions focusing solely on changes in kinematic data. The participants' kinematic measurements revealed a relation between their functional performance under assessment and their action-perception couplings while learning (Huinink et al., 2016). Along these lines, Bloomer and colleagues (2020) trained six right-handed subjects with a body-powered prosthesis over 10 two-hour sessions with the objective of analyzing motor learning on the level of joints. Motor learning outcomes were measured by inserting measurements of degrees of freedom and joint range of motion into mathematical formulas for normalized jerk and path length (Bloomer, Wang, & Kontson, 2020). However, these prior efforts had limited sample sizes and importantly did not examine MWL.

## 1.5 Research Aims and Hypothesis

Based on the literature reviewed above, it appears that there has been a limited effort to examine the concurrent changes of performance and MWL by combining EEG and behavioral analysis in a context of motor learning. This effort has been even further limited when studying motor learning through multiple practice sessions. In addition, and critical to this work, no study has examined the changes in MWL while individuals learn to operate prosthesis devices. As such, there is a critical need to examine both the changes in performance and MWL when individuals learn over multiple sessions to operate upper-limb prostheses.

Therefore, by combining neurophysiological (EEG) and behavioral (survey, kinematics) analyses, this research aims to examine the cognitive-motor learning processes underlying the concomitant performance and MWL dynamics that occur when individuals learn over multiple practice sessions to operate an upper-limb bypass prosthesis to perform a wide variety of motor tasks of daily living. Although the present research project includes multiple components, for clarity and conciseness here our specific aim will be to uniquely focus on the changes of behavioral performance and MWL as indexed by EEG and surveys during the early and late period of prosthesis learning when executing the well-established blocks and box task. To do so, we will measure changes in brain dynamics using EEG (high-alpha power) and the NASA-TLX survey (mental demand dimension) to assess MWL and behavioral performance (number of objects transported for a fixed time period) while participants perform the blocks and box task before and after having completed multiple practice sessions learning to use either a body-powered or myoelectric bypass prosthesis. In particular, it was hypothesized that from the early to late learning period, if individuals successfully acquire the novel sensorimotor skill (regardless of the type of prosthesis), the motor performance will improve (as indexed by an elevation of the number of objects transported within a fixed time period) and MWL will be attenuated (as indicated by an elevation of EEG high-alpha power and survey scores reflecting a decreased perceived MWL).

This work can inform our understanding of the cognitive-motor learning processes underlying performance and MWL during upper-limb prosthesis training and more generally understand human adaptive motor behavior. This work can also inform rehabilitation to provide amputees a more effective way to be trained in using prostheses as well as improve prosthetic design and evaluation.

# Chapter 2: Methodology

## 2.1 Participants

Six right-handed, English-speaking, able-bodied participants (age range: 21-32 years old) recruited from the University of Maryland were asked to complete tasks while seated and while using a bypass prosthesis during each of eleven sessions over the course of 6-10 weeks. None had any debilitative cognitive or physical conditions. All the participants included in this analysis identified as female. Five participants identified as white and one participant identified as Asian. The sessions included training, assessment, and/or both. Participants performed tasks using a body-powered bypass (3 participants) or a myoelectric bypass prosthesis (3 participants). Each participant reviewed and signed a consent form at the beginning of the study. This study was approved by the IRB of the University of Maryland.

## 2.2 Experimental Design

The experimental design had a first and a second component, which allowed us to examine learning and then performance under various demands. For clarity and conciseness, only the learning component of the study will be described below. Due to time constraints, this report examines only a subset of a larger dataset and specific elements of interest. The larger dataset includes EEG and survey data from an additional session 1-2 weeks after the eleventh session. The participants were asked to perform a new assessment, the Household Items Transport Task (HITT). While the twelfth session focuses more on the underlying cognitive factors associated with performance, this thesis focuses on these factors associated with training. The training schedule for each participant is shown in Figure 1.

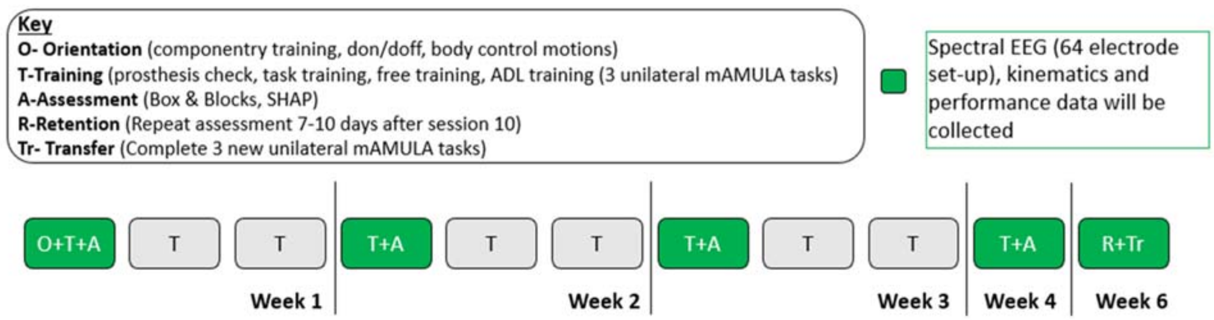


**Figure 1:** Experimental design to assess performance and MWL during learning. Session 1 consists of orientation, training, and assessment by the BBT and SHAP. Sessions 4, 7, 10, and 11 include training and assessment by BBT and SHAP. Spectral EEG, kinematic, and performance data are collected during sessions 1, 4, 6, 10, and 11. All other sessions are dedicated to training.

### 2.2.1 Training

Each of the first ten sessions involves a three-part training program. Part 1 is object manipulation with either body-powered or myoelectric bypass prostheses (Figure 2). The participant is asked to complete nine tasks: three direct grasping tasks; three indirect grasping tasks; and three fixation tasks, not necessarily in that order. A direct grasping task requires the participant to pick up an object using the bypass prosthesis. An indirect grasping task requires the participant to use their free hand to place an object into the prosthetic device. A fixation task requires the participant to use the prosthesis to stabilize an object while completing the task with their free hand.

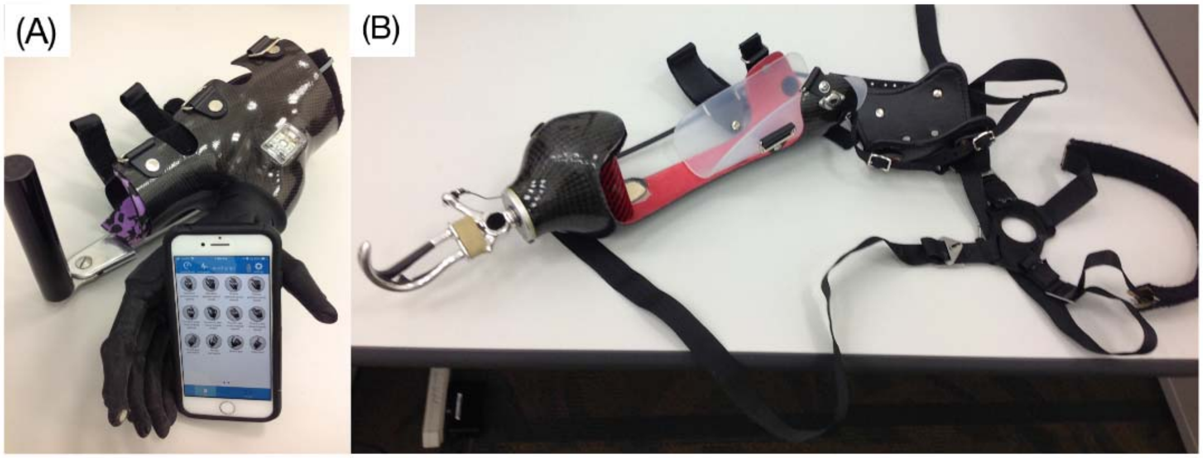


**Figure 2:** Bypass prostheses that participants had to learn to operate over the multiple sessions. (A) Bypass myoelectric prosthesis in which the hand terminal device is controlled by collecting and processing EMG from the participants' upper limb muscles. An iPhone application was used by participants to set the hand grip. (B) Bypass body powered prosthesis in which the hook terminal device is controlled by cables and pulleys via the body motion.

Part 2 of the training program is free training. The participant is given five minutes to practice using the bypass prosthesis how they see fit. During this part of the session, several objects are placed in front of the participant, who is encouraged to engage with the objects in the allotted time (Figure 3). Part 3 of training requires the participant to complete Activity of Daily Living (ADL) tasks for twenty minutes. In ADL training, there are a total of 12 tasks: 6 unilateral and 6 bilateral. The participant will attempt as many tasks as they can in the twenty-minute time frame. A unilateral task requires the participant to use only the prosthesis when completing the task whereas a bilateral task permits the use of both the prosthesis and the participant's free hand for completion (Figure 1).

**Figure 3:** Participant completing free training.

## 2.2.2 Assessment and retention

Sessions 1, 4, 7, 10, and 11 involved a period of assessment. Each participant's motor learning progress was assessed using the Box & Blocks Test (BBT) and the Southampton Hand Assessment Procedure (SHAP) (Figure 4). During sessions 2 and 11, participants were also assessed using the Jebsen Hand Function Test (JHFT) to measure and distinguish early versus late learning (Figure 1).

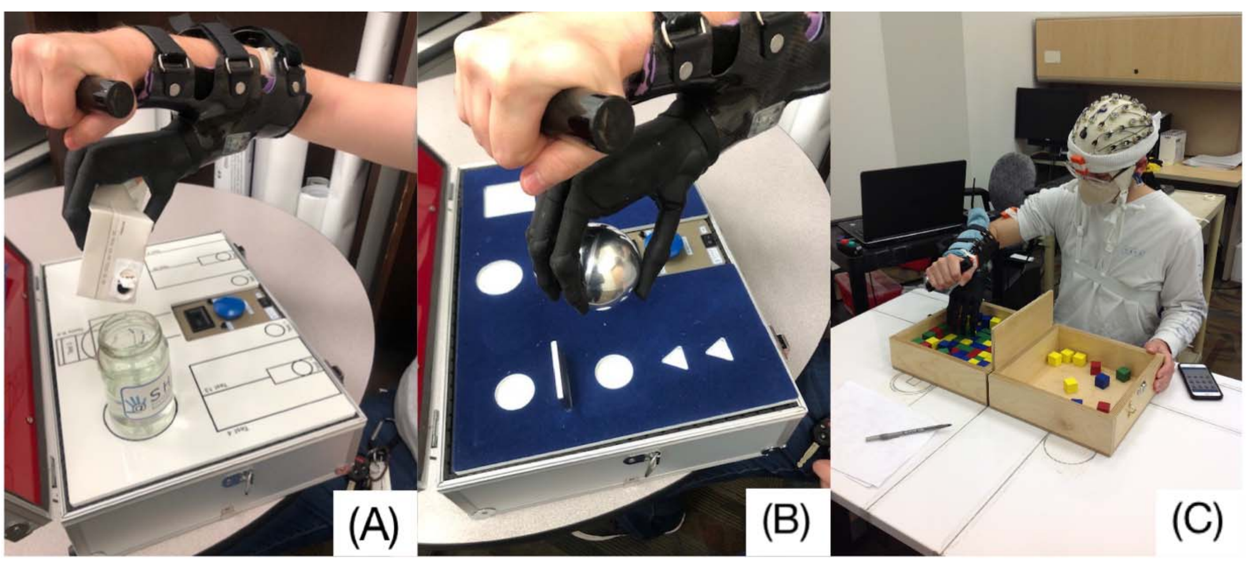


**Figure 4:** (A & B) Participants using the myoelectric bypass prosthesis to complete tasks for the SHAP. (C) Participant using the myoelectric bypass prosthesis to complete the BBT.

# 2.3 Data Collection

## 2.3.1 Performance metrics

The time to complete each task was collected using a start/stop timer. In addition, three inertial measuring unit (IMU) sensors were placed on the participant to measure kinematic quantities. One IMU sensor was placed on the bypass prosthetic device above the participant's thumb, the second was placed on the participant's mid-arm, and the third was placed on a headband on the participant's forehead. The motion of the head was measured so it could be filtered out of the EEG data to remove signal contamination if needed.

## 2.3.2 Mental workload metrics

During assessment, participants were administered the NASA-TLX survey and the Prosthesis-Orthosis Load Index (POLI) survey in intervals to assess their perceived MWL. The POLI is a survey adapted from the NASA-TLX for prosthesis users. The NASA-TLX asks the subject to rate their mental demand, physical demand, temporal demand, performance, effort, and frustration on a 7-point, 21-gradation scale with increments from very low to very high. The POLI uses a similar scale but asks subjects to rate their mental planning demand, grasp and release demand, positioning demand, performance, effort, and perceived task complexity. The definition for each dimension was standardized. These two surveys were administered once after two trials of the BBT, six times during the SHAP, and twice during the JHFT (Sears & Chung, 2010; Light, Chappell, & Kyberd, 2002; Haverkate, Smit, & Plettenburg, 2016).

For all sessions involving assessment, participants were fitted to an EEG cap (Brain Vision LLC, Morrisville, NC) to measure cortical dynamics. Head circumference and distance from the inferior nuchal line to between the eyebrows were measured to inform cap size and placement. A high-density array of 64 EEG channels was used, and 30 second recordings with eyes open and eyes closed were taken as a baseline at the beginning of each session involving assessment. As real-time EEG data was recorded, the start/stop times of each task was marked using event triggers.

## 2.4 Data Analysis

### 2.4.1 Performance metrics

As mentioned above, several tasks were considered in this work; however, due to time constraints, only the data processing for the BBT task will be presented here. For each participant, as well as both prosthesis types, the number of blocks transported across a partition in one minute were computed for the early and late practice period. So long as a block was carried across the partition, it was counted, and if two blocks were picked up at the same time, they were counted as one. Two trials of the BBT were averaged for the early and late practice period, respectively.

### 2.4.2 Mental workload metrics

Although we examined each dimension of the two surveys administered, we are primarily focused on the first dimension of mental demand for the NASA-TLX and mental planning demand for the POLI. The other dimensions were exploratory. For each participant and both prosthesis types, this mental demand dimension was computed for early and late practice. Then, the average across participants was computed.

EEG data for the BBT was recorded at a 1000 Hz sampling rate. Data was re-referenced to an averaged ear montage and was offline band-passed filtered with a low cutoff of 0.1 Hz and a high cutoff of 55 Hz with a 48-dB rolloff. The data was then resampled to 500 Hz. Independent Component Analysis (ICA) cleaning was completed to reject ocular, muscular, heart, and line noise artifacts. Epochs were visually inspected to remove any remaining artifact. The data was segmented into the movement execution phase based upon IMU markers based upon the start and end of the Box and Block trial. Spectral power was calculated across 1-Hz bins and summed across the frequency bandwidths theta (4–7 Hz), low-alpha (8–10 Hz), high- alpha (11–13 Hz), low beta (14–22 Hz), high beta (23-35 Hz), and gamma (36-44 Hz). The EEG power values were natural log-transformed prior to conducting statistical analysis.

### 2.4.3 Statistical analysis

As previously mentioned, for clarity and conciseness, only the performance, NASA-TLX, and high-alpha power will be examined during execution of the BBT during the early and late learning stage. Namely, to determine changes that occurred over the course of the training sessions, a statistical analysis was conducted to compare the performance metrics (number of blocks transported) and MWL metrics (NASA-TLX and EEG high-alpha power) between early (i.e., first practice session; session 2) and late (i.e., last practice session; session 11) learning. The primary measurement for this survey was the mental demand dimension since it was suggested as the one most related to MWL (Shaw et al., 2018; Shuggi et al., 2019). The other dimensions were examined in an exploratory manner. The average number of blocks transported and mental demand (as well as the other dimension) subscale score of the NASA-TLX were contrasted by means of paired t-test or signed rank Wilcoxon test depending on if the normality assumption (assessed via the Kolmogoroff-Smirnov test) was met or not. In addition, a 2 PERIOD (Early, Late) X 2 HEMISPHERE (Left, Right) X 5 REGION (Frontal, Central, Temporal, Parietal, Occipital) analysis of variance (ANOVA) test was employed to compare changes in high-alpha power over the course of learning. When the sphericity assumption was not met, the correction was conducted employing the Greenhouse-Geisser correction; in this case the corrected p values and degrees of freedom are reported. The effect sizes were reported for all the analyses. The significance threshold was set to $p < 0.05$ for all analyses.

# Chapter 3: Results

## 3.1. Performance

The statistical analysis of the performance revealed a significant elevation of the number of blocks transported from the early to late learning period ($p = 0.036$; $d = 2.097$). The average increase of the number of blocks transported was 9.083 ± 2.501 blocks between early and late learning (Figure 5). The Kolmogorov-Smirnov test resulted in a p-value of 0.031, which violates the normality assumption. Thus, the Wilcoxon test was performed on the data to account for the abnormal distribution.

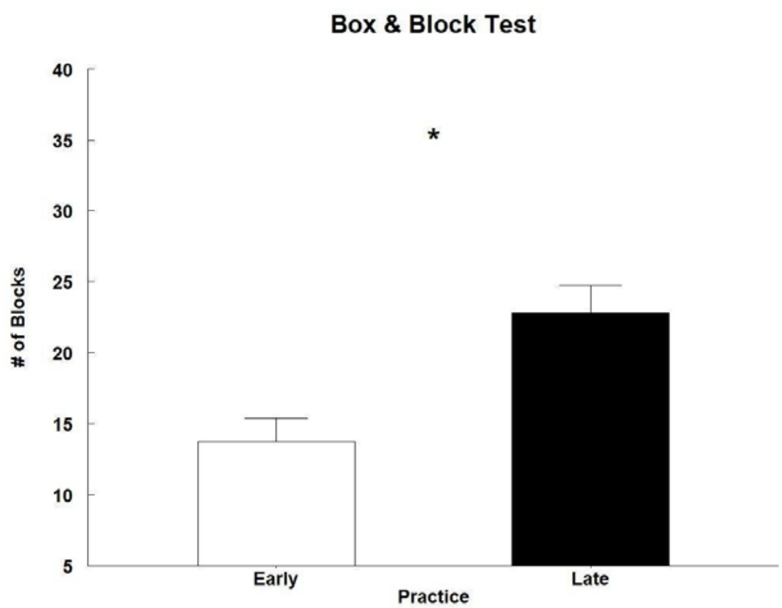


**Figure 5:** Performance results for average number of blocks moved in box and blocks test during early (white bar) versus late (black bar) learning periods. During the early learning period (session 2), an average of 13.75 ± 1.621 blocks were transported, but by the late learning period (session 11), that number increased to 22.833 ± 1.905. *: $p \leq 0.05$; **: $p \leq 0.01$; ***: $p \leq 0.001$.

## 3.2. Mental Workload

### 3.2.1 Surveys

The analysis of the NASA-TLX revealed a significant attenuation of the perceived mental demand from the early to late learning period ($t(5) = 4.663$; $p = 0.006$; $d = 1.696$) which corresponded to a reduction of the average perceived mental demand score from 35.833 ± 7.897 to 10.000 ± 3.873. The Kolmogorov-Smirnov test for all survey data resulted in no violations of the normality assumption, and a t-test was performed to determine the significance between sessions 2 and 11. Perceived physical demand from early to late learning period also showed change, but short of that of the mental demand ($t(5) = 3.152$; $p = 0.025$; $d = 1.404$). This corresponded to an attenuation of the average physical demand from 50.833 ± 11.505 to 20.000 ± 5.323 for the early and late learning stages, respectively.

The temporal demand and frustration subscale of the TLX had a p-value close to 0.05, indicating strong tendency. Although not statistically significant, the perceived temporal demand ($t(5) = 2.369$; $p = 0.064$; $d = 0.681$) and level of frustration ($t(5) = 2.114$; $p = 0.088$; $d = 01.326$) tended to decrease as participants learned to use the device from early (Temporal demand: 51.666 ± 9.458; Frustration 36.666 ± 9.545) to late (Temporal demand: 34.166 ± 11.432; Frustration: 12.500 ± 4.425) learning. Perceived effort ($t(5) = 1.739$; $p = 0.014$; $d = 0.723$) and performance ($t(5) = 1.481$; $p = 0.199$; $d = 0.873$) revealed no significant change between early (Effort: 56.666 ± 10.853; Performance 33.333± 8.333) and late (Effort: 39.166 ± 8.796; Performance: 20.000 ± 2.887) sessions (Figure 6).

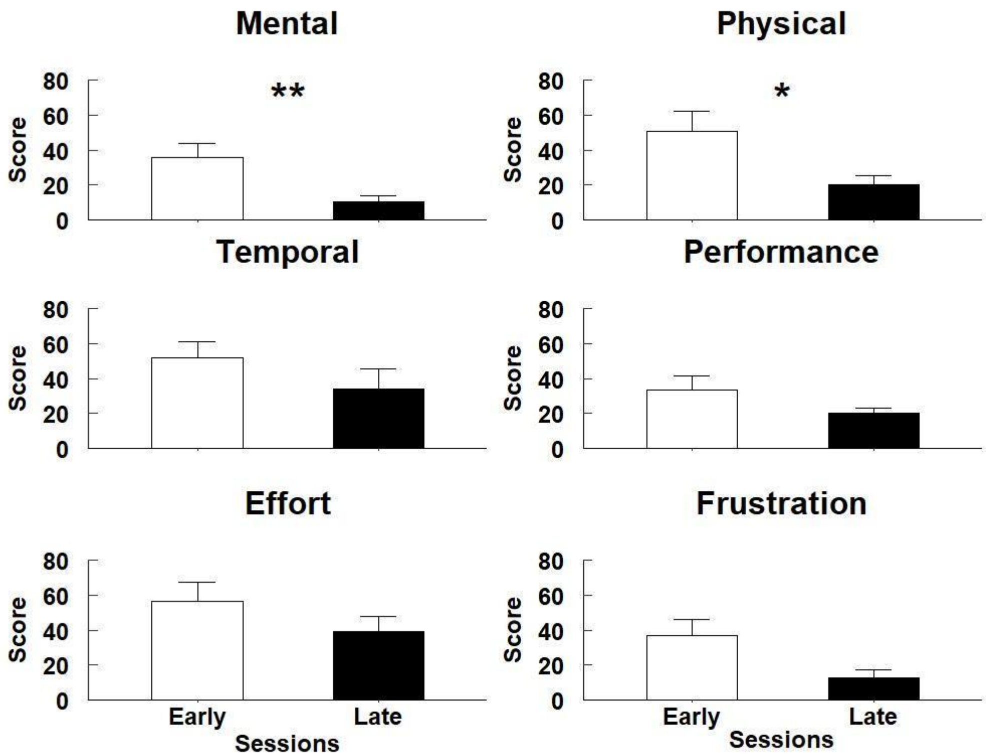


**Figure 6:** Survey results for all six dimensions of NASA-TLX (mental, physical, temporal, effort, performance, and frustration) during early (white bars) versus late (black bars) learning periods. *: $p \leq 0.05$; **: $p \leq 0.01$; ***: $p \leq 0.001$.

### 3.2.2 EEG

The only result relevant to our predictions revealed by the statistical analysis was a tendency of elevation of the high-alpha power from the early to late practice period for all cortical regions ($F(1,5) = 6.020$, $p = 0.058$, $\eta_P^2 = 0.550$) (Figure 7).

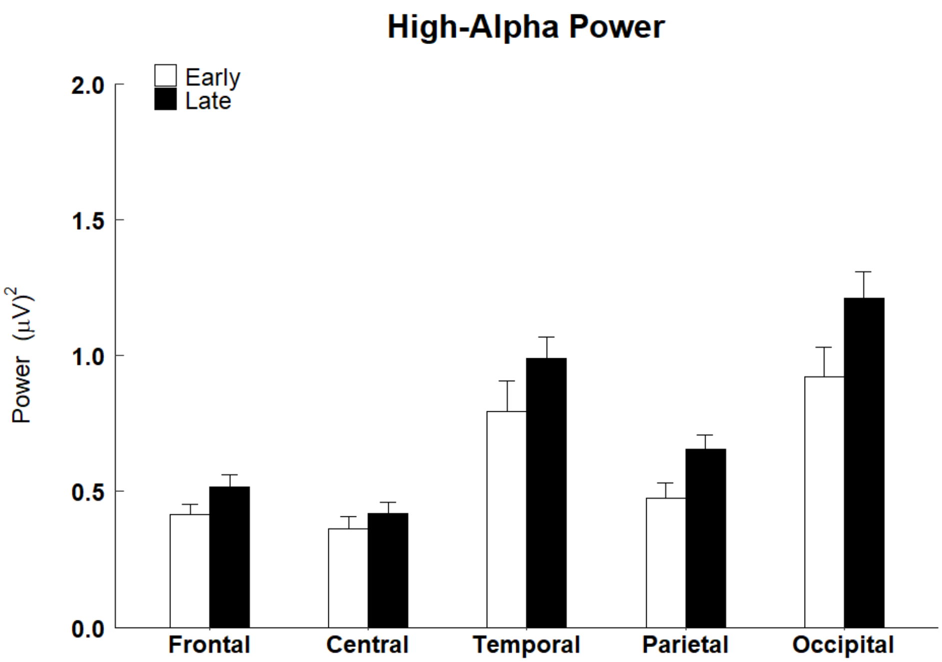


**Figure 7:** Changes in high-alpha power for the early (white bars) and late (black bars) learning periods in the frontal, central, temporal, parietal and occipital regions. *: $p \le 0.05$; **: $p \le 0.01$; ***: $p \le 0.001$.

# Chapter 4: Discussion, Conclusions, and Future Work

Our findings revealed that from early to late learning, performance was enhanced as indicated by the increased number of blocks transported in the BBT along with a reduced level of MWL which was also accompanied by a decrease in perceived physical demand. The decrease of MWL was indexed by an attenuation of the perceived mental demand as well as a tendency of elevation of high-alpha power which, although not significant, was accompanied by a substantial effect size.

## 4.1 Performance and Mental Workload Dynamics during UL Prosthesis Training

The performance improvement with a reduction of MWL is consistent with similar prior work which either 1) investigated both performance and MWL outside of prosthesis contexts (Gevins et al., 1997; Jaquess et al., 2018; Shuggi et al., 2019; Smith et al., 2001), or 2) investigated prosthesis performance without accounting for MWL (Bloomer, Wang, & Kontson, 2018; 2020). Thus, this work both confirms and extends prior work by combining performance and MWL assessment. A potential mechanism to explain these changes would be that at the beginning of the learning period, individuals who face a novel mapping between the body motion (for body-powered prosthesis users) or EMG (for myoelectric prosthesis users) signals and the prosthesis outputs not only produce a poor performance but also engage heavily their cognitive-motor resources (e.g., attentional, action monitoring, sensorimotor integration) to acquire such a mapping (Shuggi et al., 2019; Sweller, 2010; Wickens, 2002; Young et al., 2015). However, by late learning, these individuals have likely acquired this new sensorimotor mapping resulting in a better performance along with a reduction in the engagement of their cognitive-motor resources resulting in a lower level of MWL (Casadio, Ranganathan, & Mussa-Ivaldia, 2012; Jaquess et al., 2018; Shuggi et al., 2019). Such an improved performance along with a decrease in MWL from early to late learning suggests the emergence of a higher cognitive-motor efficiency (Hatfield et al., 2020; Jaquess et al., 2018; Shaw et al., 2018; Shuggi et al., 2019). In addition, when facing this novel sensorimotor challenge imposed by the prosthesis during early learning, individuals' poor performance was likely accompanied by exploration of novel body/muscle coordination to operate the prosthetic device. By late learning, the performance was enhanced and generated with more refined coordination of the body/muscles to operate the device resulting in a reduction of the perceived physical demand. However, due to a limited sample size, it is not clear if the changes in performance, MWL and physical demand differ between the body-powered and myoelectric prosthesis' users.

## 4.2 Applications to UL Amputees

The collective measurement of performance and MWL could inform training of UL amputees since it provides a more comprehensive assessment of the cognitive-motor behavior beyond what the behavioral performance alone can offer. For example, evaluating whether a desired level of psychomotor efficiency is reached during training could help determine if further training would be needed. Similarly, the combined performance and MWL assessment could also inform the design/evaluation of the potential MWL required to operate prosthetic devices.

## 4.3 Conclusion, Limitations, and Future Work

Overall, as predicted, the results of this study suggest that prosthesis performance while executing the BBT revealed significant improvement (as indicated by a greater number of blocks transported) as well as a reduction of MWL (reduction of the mental demand score of the NASA-TLX, tendency of elevation of high-alpha power) over the 11 sessions during the 6-10 week learning period. This suggests that the deployment of cognitive-motor resources (e.g., attention, action monitoring) decreased as individuals learned how to operate their prosthetic device.

This study currently has several limitations. A first limitation of this study is its relatively small sample size, which not only make the results unstable (e.g., inconsistency in the various dimensions of the NASA-TLX) but also preclude the ability to separately examine the individuals trained with body-powered and EMG-driven prostheses. Such a limited sample size is due to the nature of data collection which requires a significant time commitment, and time constraints only allowed for the data processing of six participants. Currently, additional participants are being collected to expand this sample size to allow for further confirmation of the results. A second limitation is that kinematic data was not analyzed here. Such an analysis would be useful to further understand the reduction of perceived physical demand by examining the changes in physical effort and more generally the performance dynamics during training. Future efforts will also analyze the IMU data to derive additional biomechanical metrics (e.g., smoothness). A third limitation is that the EEG analysis was limited to one frequency band; however, additional analyses are underway to account for other bandwidths (e.g., theta, low-alpha). A fourth limitation is that the use of bypass prostheses by able-bodied participants may not take into account other important factors affecting UL amputees learning to use prostheses. Thus, future research should also include a comparison of results between able-bodied participants and upper limb amputees to study the translatability of the results.

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# Appendix A: Equity Impact Report

Systemic racism has been historically present in the field of neuroscience. Research in this area has been driven by processes of racialization and used to justify white supremacist ideologies. Communities of color have been alternately exploited by and excluded from neuroscience research (Abiodun, 2019). As researchers in this field, we share a responsibility and moral imperative to build a more equitable future in neuroscience and hold ourselves accountable for the impacts of our research. Drawing from the Racial Justice Impact Assessment framework developed by Race Forward: The Center for Racial Justice Innovation (Keleher, 2009), the following section examines diversity in our participant sample, potential adverse and equitable impacts of our research, and accessibility in the dissemination of our results.

## Diversity in the Participant Sample

In 2005, an estimated 1.6 million people were living with limb loss in the United States, and even more are expected to be living with limb loss today. Approximately 42% of those individuals are nonwhite (Ziegler-Graham et al., 2008). It is critical that prosthesis research reflects the diversity of prosthesis users. Nevertheless, demographic reporting in neuroimaging research is rare. As in our study, neuroimaging methodologies such as EEG are often employed in prosthesis research. Of 99 high-impact articles published between 1990-2020 that used EEG, only six reported the racial demographics of their research participants, and they tended to show a bias toward white participants (Goldfarb, 2021). Goldfarb calls for increased transparency with respect to reporting demographic information in neuroimaging studies, as environmental and genetic variables associated with different demographic groups can impact the generalizability of research findings (2021). Consistent with this recommendation, we have reported the racial/ethnic and gender identities of our research participants (see section 2.1, Participants).

EEG data collection requires that consistent contact be made between a participant's scalp and an EEG cap worn on the head. Coarse and curly hair textures, as well as hairstyles such as braids and cornrows most commonly worn by African American participants, can complicate the ability to make direct contact between the scalp and the EEG electrodes. As a result, some researchers exclude individuals with these hair characteristics from participation in EEG studies, which leads to an underrepresentation of African Americans in this field of research (Choy, Baker, & Stavropoulos, 2021). While our study did not exclude participants with African hair types or hairstyles, we did not make intentional attempts to recruit participants from the African American community.

We acknowledge that, as a result of our small sample size and strategy of recruiting participants from a predominantly-white college campus, our sample is not representative of the diversity within the population of prosthesis users. No male participants were included in our analysis, and people of color were underrepresented. This may negatively impact the ability to generalize our findings to the broader population. Yancey, Ortega & Kumanyika (2006) emphasize the importance of strong relationships between researchers and participant communities in engaging minoritized individuals in research. In future work, a more representative sample may be obtained by increasing the sample size and working with leaders in communities beyond the University to recruit study participants.

**Potential Adverse and Equitable Impacts of the Study**

In addition to adding to the body of knowledge on motor learning, one goal of our research is to inform upper limb prosthesis training. The overall rate at which those with upper limb loss abandon prosthesis use is estimated to be at least 20% (Biddiss & Chau, 2007). However, training with the prosthesis device when it is first received is associated with greater satisfaction (Resnik et al., 2020). Therefore, more effective training is expected to improve users' experience with prosthetic devices and reduce their likelihood of abandoning their prostheses.

More efficient training is also expected to reduce the high costs associated with prosthetic devices. According to a 2011 survey, the overall mean cost of an upper limb prosthetic device is $9574, with electric prostheses being even more costly. Some participants reported initial costs of up to $40,000. Maintenance presents an additional cost, ranging from $100-10,000 each year (Biddiss et al., 2011). Clearly, there is a high economic barrier to prosthesis adoption and continued use, producing disparities in access to this technology between individuals with upper limb loss of different socioeconomic statuses. While our research does not directly address the costs of prostheses and their maintenance, we hope that our research can inform more efficient training for new prosthesis users, thus helping to reduce these healthcare costs and narrow the gap in access to assistive technology.

A survey of 449 upper limb prosthesis users found that Black participants were less likely to be satisfied with their device (Resnik et al., 2020), increasing the chance of prosthesis abandonment. While the reason for this discrepancy in relation to prosthesis use has not been studied, we speculate that it is a result of the long history of distrust among Black people toward medical systems (Gamble, 1997). Considering that this community was underrepresented in our sample, future studies combining both behavior and EEG as done here are needed to examine how the current results may be modulated for populations of other ethnicities, races, cultures, and socioeconomic statuses.

**Accessibility of Research Findings**

In the same spirit of equity and accessibility that has driven other steps of our research process, we are taking measures to improve accessibility in the dissemination of our research findings. First, we are depositing our thesis in the Digital Repository at the University of Maryland, which will provide the public with open access to our work after a temporary embargo. This removes financial barriers to access, and allows those outside of academia to view the document. Second, our thesis was written to be accessible to those with vision impairments. Each figure is accompanied by a description and alternative text that can be read by screen reader software. Finally, we plan to post a plain-language summary of our research to our website, https://gemstoneteamreach.wixsite.com/2022/, following the Federal Plain Language Guidelines (2011). This will help increase accessibility of our research findings to those without formal scientific training.

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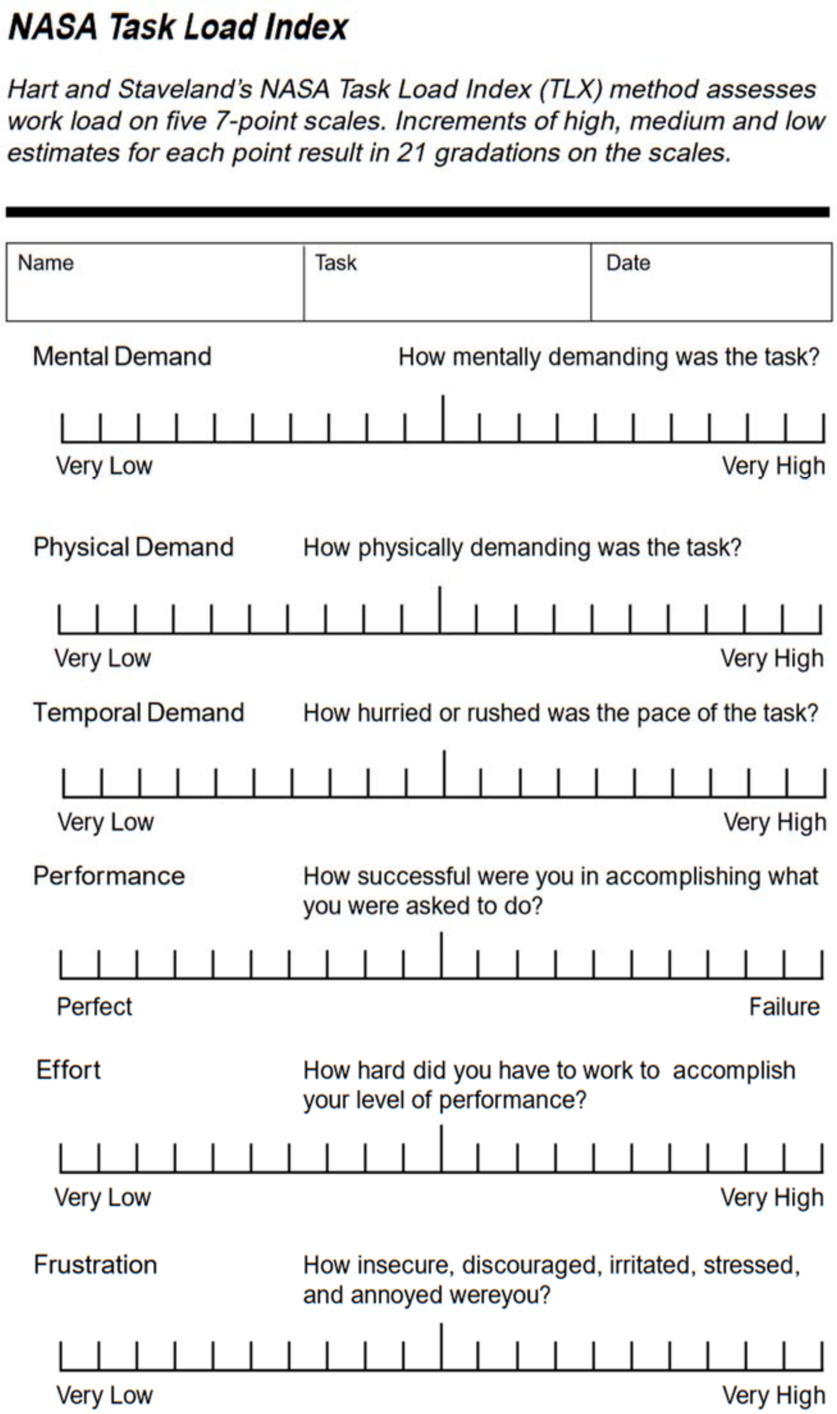
## Appendix B: NASA Task Load Index (NASA-TLX)



### *NASA Task Load Index*

*Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.*

| Name | Task | Date |
|---|---|---|
| | | |

Mental Demand — How mentally demanding was the task?

Very Low — Very High

Physical Demand — How physically demanding was the task?

Very Low — Very High

Temporal Demand — How hurried or rushed was the pace of the task?

Very Low — Very High

Performance — How successful were you in accomplishing what you were asked to do?

Perfect — Failure

Effort — How hard did you have to work to accomplish your level of performance?

Very Low — Very High

Frustration — How insecure, discouraged, irritated, stressed, and annoyed wereyou?

Very Low — Very High

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