ABSTRACT

Title of Dissertation:	EXAMINATION OF COGNITIVE-MOTOR PROCESSES DURING REACHING MOVEMENTS: FROM INDEPENDENT HUMAN PRACTICE TO HUMAN-ROBOT TEAM PERFORMANCE
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While many studies used electroencephalography (EEG) to assess mental workload during performance, a fairly limited effort examined this notion in a context of i) practice and ii) team dynamics. Of these limited studies, none employed a combined approach to assess mental workload throughout motor practice. Therefore, the first study aimed to examine whether a combined evaluation of attentional reserve and cognitive-motor effort could collectively assess mental workload dynamics during practice of a novel task. Also, among the limited examination of mental workload and performance in team environments, no work has manipulated interdependence while accounting for psychological factors such as self/collective efficacy, attribution and trust. Thus, the second study aimed to investigate performance, mental workload and these psychological factors while varying interdependence. We employed a human-machine interface where participants learned to perform reaching movements with a virtual robotic arm via limited head motion allowing examination of cognitive-motor practice. Then, once participants learned to control the effector, its controller was manipulated to serve as a synthetic teammate to perform the task with human participants. Three interdependence levels were considered: the human (H-r) and synthetic (h-R) teammate mostly controlled the arm as well as a shared (h-r) control condition. Performance was assessed via the arm kinematics and mental workload via the novelty-P3 and EEG spectral power. Surveys assessed mental workload and psychological factors. A de-noising algorithm allowed removal of artifacts from the EEG signals due to head motion from controlling the effector. The first study suggests that throughout practice the proposed approach could capture an elevation of attentional reserve and an attenuation of cognitive-motor effort, which collectively index a reduction of mental workload along with improved performance. The second study suggests that while the h-r and h-R conditions revealed similar kinematic performance, mental workload and trust, a lower sense of attribution (personal) was observed for the h-R compared to the h-r condition. Additionally, the H-r condition showed the worst performance and highest mental workload. Thus, the h-r interdependence level may provide the best cognitive-psycho-motor performance. Together these studies can improve understanding of cognitive-psycho-motor mechanisms as well as inform the design of assistive technology.

EXAMINATION OF COGNITIVE-MOTOR PROCESSES DURING REACHING MOVEMENTS: FROM INDEPENDENT HUMAN PRACTICE TO HUMAN-ROBOT TEAM PERFORMANCE

by

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Dedication

This work is dedicated to my family who has supported me throughout all of my graduate studies.

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Chapter 1: Introduction

Humans are highly capable of adapting their motor behavior; such a capability is dependent on various cognitive-motor processes. These mechanisms are employed in situations where task demands increase due to changes in the environment (e.g., task difficulty, dealing with novel challenges, team environment; Miller et al., 2014; Rietschel et al., 2012; Shuggi et al., 2017; 2018; 2019). Namely, the modulation of resource allocation to face task demands is crucial to the adaption of cognitive-motor performance under various levels of challenge since resource allocation can drive changes in mental workload and performance (Gentili et al., 2013, 2015; Rietschel et al., 2014; Shewokis et al., 2015; Wickens, 2002, 2008). Therefore, an increase of task demands can result in an elevation of mental workload due to an augmentation of the engagement of processing resources, which if saturated may become less efficient and lead to a decrease in performance (Gentili et al., 2014; Guadagnoli & Lee, 2004; Rietschel et al., 2011). As such, mental workload can be described as a multidimensional construct resulting from the connection between task demands and the recruited cognitive (e.g., attentional, working memory), sensory (e.g., visual, proprioceptive), and motor (e.g., motor planning and coordination) resources in order to attempt to maintain performance (Paas & van Merrienboer, 1994; Van Gog & Paas, 2008; Wickens, 2002, 2008; Young et al., 2015).

The concurrent examination of mental workload and performance is highly relevant for the understanding of cognitive-motor processes during performance and learning when individuals engage in task execution alone or in a team context. In this dissertation, a first investigation will examine mental workload and performance dynamics in a context of practice where individuals had to develop a new motor skill. Then, in a second study, once individuals were trained, changes in mental workload and performance along with specific psychological factors critical for team dynamics were examined while the dependency of teammates was manipulated. Thus, the first main section (section 1.1) provides a review of the relevant literature about mental workload in the context of cognitive-motor performance and practice when individuals perform alone. This review highlights gaps in the literature and outlines the specific aim for the first study. The second main section (section 1.2) reviews the relevant literature related to mental workload in the context of team dynamics in order to identify the gaps and generate the specific aim for the second study. Lastly, the third main section (section 1.3) briefly presents a unique human-machine interface, which can be used to address both specific aims and generate our predictions.

1.1 Mental workload in the context of cognitive-motor performance and learning

Aside from a large body of behavioral investigations, numerous studies have examined mental workload via electroencephalography (EEG) while a single person performs a task; however, few studies have used a combined approach of examining attentional reserve as well as cognitive-motor effort (Bradford et al., 2019; Gentili et al., 2018; Shaw et al., 2018). Recently, Shaw and colleagues (2018) used a combined approach, employing the component amplitudes of the event-related potential (ERP) waveform to examine attentional reserve and spectral power to assess cognitive-motor effort. Specifically, these metrics were assessed during performance of a cognitive task at two levels of difficulty while walking and seated. Their combined approach primarily utilized the novelty-P3 component (attentional reserve) and the frequency bands theta and low-/high-alpha (cognitive-motor effort) to provide a robust assessment of mental workload. In particular, by employing such a combined approach these few previous studies revealed that as task demands increased, the attentional reserve was reduced (i.e., decrease of novelty-P3 amplitude) along with increased cognitive-motor effort (i.e., attenuation of low-/high-alpha; increase of theta power), which was collectively indicative of an elevation of mental workload. This work showed the benefits of a combined approach to provide a robust index of mental workload during cognitive-motor performance, even in tasks susceptible to environmental noise (i.e., walking on a treadmill).

Although mental workload has been comprehensively studied in the context of performance including studies that have used a combined approach, a relatively limited number of studies have assessed mental workload in the context of motor practice (e.g., Akizuki & Ohashi, 2015; Gentili et al., 2011; JS Hu et al., 2016; Jaquess et al., 2018; Rietschel et al., 2014; Shuggi et al., 2017, 2018, 2019). Within this body of work the majority of studies have primarily focused on behavioral data by employing behavioral performance and assessing mental workload via surveys such as the National Aeronautics and Space Administration Task Load Index (NASA TLX; Akizuki & Ohashi, 2015; Hart & Staveland, 1998; Hart, 2006; JS Hu et al., 2016; Shuggi et al., 2017, 2018, 2019). Even though the NASA TLX survey presents many advantages in such a learning/practice context (see Shuggi et al., 2017 for details), a primary drawback is its subjective nature and the single time-point measurement of mental workload throughout the experiment (Gentili et al., 2014; Hart & Staveland, 1998; Hart, 2006; Ke et al., 2014).

Only a fairly limited number of studies have used EEG to examine cortical dynamics during cognitive-motor practice (i.e., Gentili et al., 2011; Gevins & Smith, 2000; Jaquess et al., 2018; Perfetti et al., 2011; Rietschel et al., 2014; Weber & Doppelmayer, 2016). EEG allows for high temporal resolution throughout the entire testing session, which is informative when examining changes in cortical dynamics throughout practice of a novel and challenging reaching task. In particular, work from Rietschel and colleagues (2014), employed several ERP components (N1, P2 as well as the novelty-P3) to assess the relationship between attentional reserve and performance as individuals practiced a reaching task, which required adaptation to a kinematic distortion. They demonstrated that the amplitude of the novelty-P3 component increased as participants learned to perform the reaching task with a visual distortion and improved their performance; thus, revealing increased automaticity of performance during late relative to early practice (Rietschel et al., 2014). Although not conducted in a specific context of mental workload, Gentili and colleagues (2011) demonstrated that as individuals adapted their reaching movements to a visuomotor perturbation, performance was enhanced along with an attenuation of cognitive-motor effort. Cognitive-motor effort was indexed by a progressive alpha and theta synchrony, thereby revealing the emergence of more automatic behavior by late practice (Gentili et al., 2011). While interesting, each of these studies separately examined the changes of attentional reserve and cognitive-motor effort. As far as we know, no prior work employed a combined assessment to examine the concurrent changes of attentional reserve and cognitive-motor effort, which can collectively index variation of mental workload along with performance dynamics during practice. Such an approach would allow for an improved understanding of cognitive-motor mechanisms throughout practice of a motor skill.

Thus, the first aim of this dissertation was to address this gap by examining the concomitant modulations of attentional reserve and cognitive-motor effort to robustly index mental workload dynamics along with changes of motor performance throughout practice.

1.2 Mental workload and psychological factors in a team context

The entire body of work previously discussed either in a performance or a learning/practice context always focused on the examination of cognitive-motor processes when individuals perform alone. However, another area of investigation where the examination of human mental workload and motor performance is relatively scarce is the situation where humans perform within a team environment (Funke et al., 2012, 2016; Guastello et al., 2015; Helton et al., 2014; Miller et al., 2013, 2014; Sellers et al., 2014).

While some studies have examined motor performance in the context of a human team such as a dyad, many did not consider changes in mental workload (Shea et al., 1999, 2000; Shebilskem et al., 1992; Wulf et al., 2010). Only a limited number of studies have considered the relationship between motor performance and mental workload in the context of a human team with only a few considering dyads (Funke et al., 2012, 2016; Guastello et al., 2015; Helton et al., 2014; Miller et al., 2013, 2014; Sellers et al., 2014; Stevens et al., 2009, 2012). For instance, Miller and colleagues

(2013, 2014) conducted two studies in which the manipulation of an adaptive and maladaptive teammate was examined during performance of a cognitive-motor task. Participants received helpful (adaptive), unhelpful (maladaptive) or no advice (neutral) from two separate teammates. Adaptive team environments can be defined by high levels of perceived competence, task cohesiveness, and trust, whereas maladaptive team environments have low levels of perceived competence, task cohesiveness, and trust (Carron, Colman, et al., 2002; Dirks, 1999; Marcos et al., 2010; Miller et al., 2013, 2014). Miller and colleagues (2013, 2014) conducted manipulation checks to confirm that the participants perceived the teammate in the adaptive condition to be more competent and trustworthy, as well as felt a higher level of task cohesion with the helpful teammate.

In the first study, Miller and colleagues (2013) found that the adaptive condition resulted in greater performance than the neutral and maladaptive condition. Additionally, they observed that the adaptive and neutral conditions led to significantly better attentional resource allocation than the maladaptive condition. Lastly, the cognitive workload levels in the adaptive and neutral condition were lower than in the maladaptive condition. Although there were no significant differences between the adaptive and neutral condition in terms of attentional resource allocation and cognitive workload, it is interesting to note that the adaptive environment had better performance, suggesting these performers may have had more attentional resources available (Miller et al., 2013).

Miller and colleagues' (2014) subsequent study incorporated EEG and found that the amplitude of the novelty-P3 component was reduced in the maladaptive condition when compared to both the neutral and adaptive conditions, confirming the results of their previous study and suggesting that in the maladaptive condition less attentional reserve is available. Taken together, Miller and colleagues' (2013, 2014) studies show the influence of trust and perceived competence on task cohesion and performance.

Additional studies have shown that trust can be an influencing factor on cohesion, specifically showing that increases in trust among team members can create an increase in cohesion (Warner et al., 2012). One study in particular revealed that collective efficacy is mainly based on trust among team members (Chou et al., 2013). Since both cohesion and efficacy are thought to have an impact on team performance, it seems valid to consider trust as a construct, which may have an indirect influence on team performance (Chou et al., 2013; Miller et al., 2013, 2014; Warner et al., 2012). Lastly, trust is critical to consider in the context of this work due to the use a synthetic partner. While it has been found that individuals working with a robot instead of a human experience lower workload levels, this is dependent on trust in automation, which is a particularly complex factor in the framework of human-robot team dynamics (Harriott et al., 2015).

It must be noted that a limited number of studies have examined cognitive workload and trust in the framework of human-robot interactions, which can also represent a form of teaming (Bailey et al., 2006; Broad et al., 2017; Hilburn et al., 1997; Kaber & Endsley, 2004; WL Hu et al., 2016; Moray et al., 2000; Parasuraman et al., 2007). However, while automation is intended to aid human users in task completion, it has been observed that implementation of a machine may actually negatively affect the human's motor performance and/or mental workload (Parasuraman & Riley, 1997; Sheridan, 2002; Shuggi et al., 2018; Wiener, 1988).

Furthermore, other psychological notions that are critical to team performance must also be considered. Namely, to our knowledge there are only a few studies, which have examined self-efficacy in a context where humans interact with a synthetic partner, to manipulate the motivation of individuals to exercise (e.g., Feltz et al., 2014; Feltz et al., 2016). While informative, this work is not sufficient to understand efficacy beliefs and their relationship to mental workload in a context of team performance with a synthetic partner. Hence, there is still a need to further study teammate interactions, especially in the context of cognitive-motor performance.

Additionally, attributions can also have a large impact on efficacy beliefs. Studies have shown that collective efficacy and sense of attribution have a reciprocal relationship (Allen et al., 2009; Chow & Feltz, 2008). Specifically, Chow and Feltz (2008) examined the influence of pre-competition collective efficacy on post-competition team attributions. They found that individual perceptions of collective efficacy predicted the attribution property of team control. In other words, individuals who were confident in their team's capabilities believed the cause of attainment to be within the team's control. They also found that teams with stronger perceptions of aggregated collective efficacy reported more stable causes of performance when compared to teams with weaker perceptions of aggregated collective efficacy. Allen and colleagues (2009) approached the attribution – collective efficacy relationship from the opposite perspective and examined the impact of team attributions on collective efficacy. They found that attributions were significantly related to collective efficacy. When considering perceptions of team control and stability concurrently, there was variability among winning and losing teams. For winning teams it was found that stable and controllable attributions were associated with higher collective efficacy. Conversely, for losing teams it was demonstrated that if control of the outcome was thought to be external to the team then the stability of the cause was irrelevant; however, if the causes were thought to be internal then a stable attribution would negatively impact collective efficacy. Thus, sense of attribution is highly relevant to efficacy and was also considered as a part of this study.

In summary, as far as we know no study has examined the cognitive-motor performance of a human by jointly examining the mental workload, self/collective efficacy beliefs, sense of attribution, trust, and motor performance in the context of teamwork. Therefore, as a first step of a programmatic approach to understanding the interaction of these elements in team dynamics, we directly manipulated interdependence between teammates (defined as the degree to which teammates have to rely on each other to complete their tasks; Saavedra et al., 1993; Thompson, 1967; Van de Ven et al., 1976).

Thus, the second aim of this dissertation was to address this gap by examining the concurrent changes in the cognitive-psycho-motor (i.e., mental workload, efficacy, trust, attribution and performance) processes while manipulating the interdependence between teammates.

1.2.1 Existing and proposed team framework

While numerous interesting frameworks have been developed to understand human team dynamics, the high complexity of cognitive-motor and psychological mechanisms in humans are magnified in a human team context, which makes their analysis very challenging.

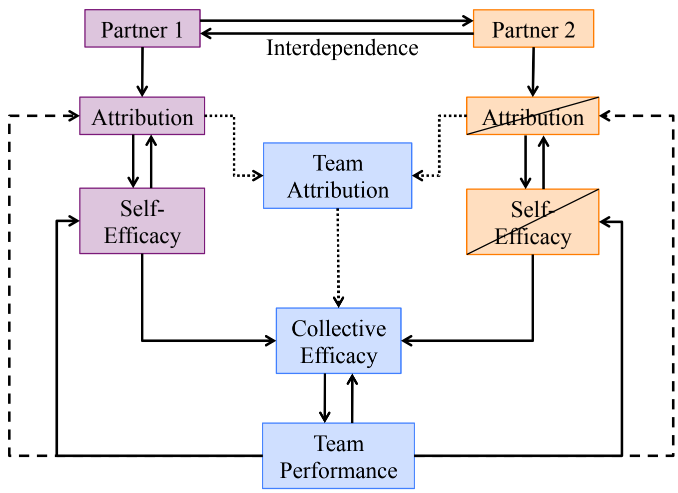


Figure 1: Partner 1 is representative of the human user, while partner 2 is representative of the synthetic partner. Use of a synthetic partner eliminates some of the complexity underlying the constructs associated with team dynamics.

Hence, in this work we have employed a synthetic partner; although this may be somewhat less realistic, it allows for greater accuracy in the manipulation of team dynamics (Shuggi et al., 2018). A synthetic teammate mitigates the complexity of having a human partner, which could create confounding factors due to complex social interactions. Specifically, instead of two humans contributing to the team attributions and collective efficacy only one human is contributing to these inherently complex constructs (see figure 1). Furthermore, although human-robot frameworks are interesting, they were initially developed to inform robotic system design improvements as well as enhance human-robot interactions with greater emphasis on the robot than the human. Such frameworks tend to include many elements, which as a first step are not necessarily critical to understanding the human mechanisms involved with human-robot interactions (i.e., You & Roberts, 2017). Hence, we have proposed a framework, which considers human-robot interactions with a greater emphasis on human characteristics such as mental workload, efficacy beliefs, sense of attribution and trust.

The proposed framework was strongly influenced by the work of Maynard and colleagues (2015) as well as You and Robert (2017). The task assigned to the human-robot team has a great influence over the rest of the framework due to the importance of task interdependence on the team (Saavedra et al., 1993; Myers et al., 2004) as well as on the individual's cognitive workload (Kirschner et al., 2009); hence, the task is presented as an input for the overall system (figure 2; box 1). The organizational context encompasses both individual and team level factors since, in this context, it is reflective of the type of training completed by the human and the robot (figure 2; box 2). The individual level factors define the human and robot's characteristics separately, while the team level factors define the elements concerned with the arrangement of the human and robot within a team context such as, but not limited to, interdependence.

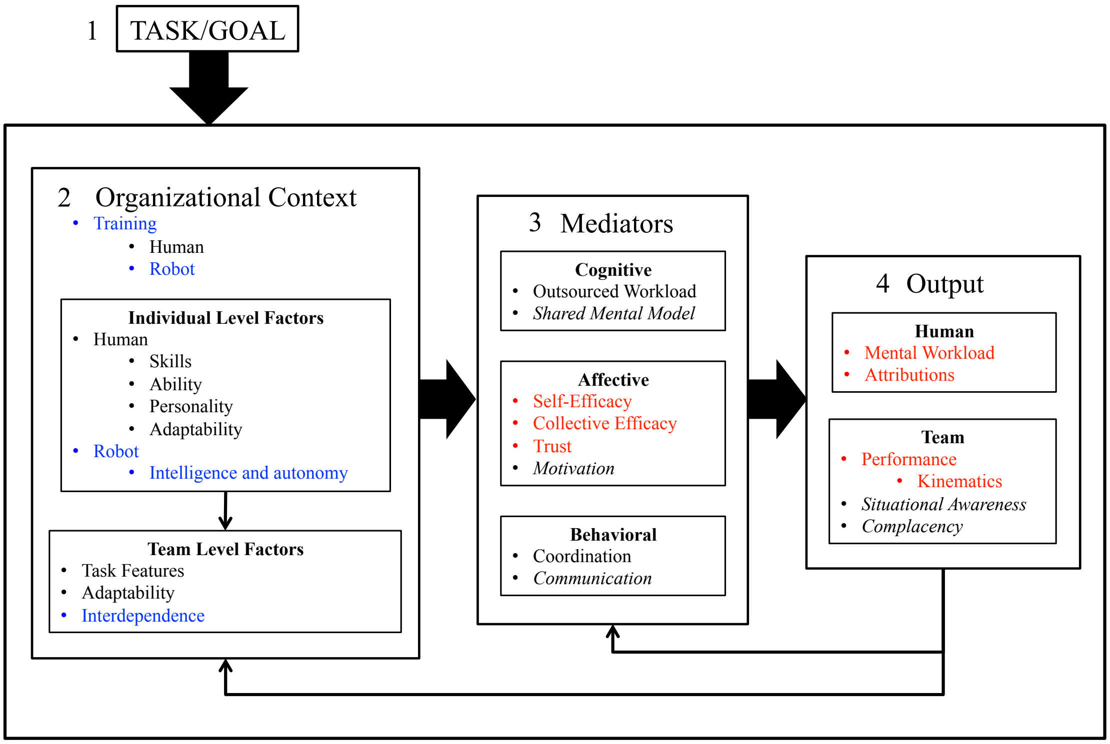


Figure 2: Proposed human-robot team framework. Italicized items are not currently assessed; items in blue were manipulated and/or controlled (interdependence and quality of robot). Items in red were measured (self/collective efficacy, trust, mental workload, attributions, performance).

The mediators are divided into the classifications of cognitive, affective, and behavioral (figure 2; box 3). In the cognitive domain, there are two elements: outsourced workload and shared mental model. Outsourced workload is reflective of the amount of workload, from which the human is relieved due to the presence of a synthetic partner. The shared mental model is currently beyond the scope of this study. The affective elements, which were examined, are self-efficacy, collective efficacy, and trust. Motivation is an important element to be considered, since it can influence performance; however, it was not a primary focus of this work (Bray & Whaley, 2001; Miller et al., 2013). Lastly, the behavioral domain includes coordination and communication. The coordination is reflective of the level of interdependence between the human and synthetic partner. When the human or robot has greater control, less coordination is required than when the human and robot must share control. Communication is also an important mediator, but is currently beyond the scope of this work.

The output of this framework is divided into human and team outcomes (figure 2; box 4). The human outcomes are mental workload, attributions, and trust. A primary focus of this work was to address the mental workload of the human and determine if the opportunity to outsource parts of the task to the synthetic partner is beneficial or a hindrance. Team outcomes include performance (i.e., kinematic performance), situational awareness, and complacency. While situational awareness and complacency are important factors to consider in any system where automation is present, it is currently beyond the scope of this study and could be better assessed when a more complex synthetic partner is used. Finally, the feedback loops are similar to those found in You and Robert's (2017) framework; however, in the framework proposed here the feedback goes to the mediators as well as the inputs enclosed within the organizational context. Given the literature of collective efficacy, it is plausible that the outcomes could influence both the individual and team level factors since both affect the mediators. This is especially true if the framework is being considered over a longer timeline (Shuggi et al., 2019).

1.2.2 Elements relevant to proposed team framework

In addition to the element of mental workload outlined for the first experiment, overviews of elements relevant to the second study are presented in this section.

1.2.2.1 Efficacy

Bandura (1997) defines two types of efficacy: self and collective. Perceived self-efficacy is defined as a person's beliefs in his or her ability to complete the required actions to achieve a goal. Perceived collective efficacy is a group's shared belief in their joint ability to complete the required actions to achieve a goal. Even though collective efficacy is a group's shared belief, it is based on each team member's views of the team's abilities (Bandura, 1997; Myers et al., 2004; Stajkovic et al., 2009). Hence, the use of a synthetic teammate does not completely undermine the construct of collective efficacy since it depends on how the human perceives the robotic teammate. Furthermore, two possible methods of measuring collective efficacy are aggregated self-efficacy and aggregated collective efficacy (Bandura 1997; Myers et al., 2004). To implement the approach of aggregated self-efficacy, each team member's belief in his/her abilities to perform within the group is assessed and then aggregated in order to obtain a representation of the team. Aggregated collective efficacy is implemented through an assessment of each team member's belief in the team's abilities and is then aggregated. In particular, it was proposed that the level of interdependence influences the measurement of collective efficacy. Namely, it has been shown that for tasks of higher interdependence, aggregated collective efficacy is a better predictor of performance (Bandura, 1997; Feltz & Lirgg, 1998; Myers et al., 2004). Thus, the measure of collective efficacy used within this work is representative of the human user's perspective on the team's abilities to complete the task. Lastly, for tasks of higher interdependence it has been suggested that as task interdependence increases, collective efficacy can become a more separate construct from self-efficacy (Bandura, 1997; Chen et al., 2002). Hence, it is possible for team members to report high (or low) self-efficacy and low (or high) collective efficacy; the two are not necessarily congruent (Chen et al., 2002).

1.2.2.2 Sense of Attribution

While the moderators of the relationship between collective efficacy and performance are important, it is also important to acknowledge factors, which may influence self and collective efficacy. One important factor is an individual's sense of attribution (Allen et al., 2009; Bandura, 1986; Chow & Feltz, 2008; Weiner, 1985). Attribution theory considers how an individual evaluates an outcome in achievement situations (Weiner, 1985). Weiner (1985) states that perceived causes of an outcome have three properties. The first property is locus of causality – whether the cause is within an individual or within the environment (i.e., internal vs. external). The second property is stability, which is the extent of variability within a cause (e.g., mood is highly variable, but aptitude is stable). Lastly, there is controllability, which determines whether the cause is voluntary or involuntary (e.g., voluntary: amount of effort exerted; involuntary: physical coordination). It has been suggested that self-attributions can be extended to team attributions since they are based on the same properties (Chow & Feltz, 2008; Weiner, 1985).

Bandura's (1986) Social Cognitive Theory proposed that although prior experience can influence efficacy, the evaluation of causes could contribute to efficacy beliefs. It was further suggested that there is a reciprocal relationship between attributions and efficacy (Allen et al., 2009). A model from Chwalisz and colleagues (1992) shows a significant reciprocal relationship between self-efficacy and two of Weiner's (1985) properties of causality, locus of causality and controllability. Through an analysis of other models this work also showed that perceiving the cause of an event as internal and uncontrollable is related to higher self-efficacy. Due to evidence of this reciprocal relationship it has been suggested that after assessing his or her performance an individual has a short-term positive or negative feeling, then defines a cause for the outcome, which leads to attribution specific emotions, such as confidence (Weiner et al., 1979). Since self-efficacy can be classified as a task specific type of confidence, which also defines levels of success (Bandura, 1997), it is possible to think of self-efficacy as an attribution. Furthermore, efficacy beliefs have been considered to be action regulators, allowing efficacy to be considered as a predictor or as an attribution (Karoly, 1993). Additionally, attribution specific emotions can be positive or negative (i.e., increases or decreases in confidence). Hence, attributions can lead to longer-lasting positive or negative emotions and behaviors (Chow & Feltz, 2008; Weiner et al., 1979).

1.2.2.3 Trust

It is important to note that while many studies have examined the relationship between trust and team performance in various capacities, a limited number of studies have examined the relationship between trust and efficacy. However, some studies have examined the influence of trust on cohesion, which can be defined as the group tendency to work together in order to achieve a goal (Carron, Bray & Eys, 2002). Cohesion is a very similar construct to collective efficacy. The subtle distinction between efficacy and cohesion is that efficacy is concerned with belief about ability to achieve a goal, while cohesion is related to actions completed to achieve a goal. It has been proposed that collective efficacy is a mediator of the relationship between cohesion and performance (Warner et al., 2012). Additionally, strong correlations have been found between cohesion and self-efficacy (Marcos et al., 2010). It has also been suggested that efficacy and trust may be the same construct (Warner et al., 2012). Lastly, it is interesting to note that trust is usually considered along two dimensions, cognitive and affective (Erdem & Ozen, 2003; McAllister, 1995). It must be noted that the use of a simple synthetic partner allows us to only assess cognitive trust, which is based on a rational reason for a person to trust someone to complete his/her work (Erdem & Ozen, 2003).

1.3 <u>Human-machine interface to inform human cognitive-psycho-motor processes</u>

To address the aims of this dissertation, we employed a human-machine interface (HMI), which has successfully been employed to examine human cognitive-psycho-motor processes during performance and learning/practice when individuals perform alone or with a synthetic partner (Shuggi et al. 2017, 2018, 2019). More specifically, this HMI requires participants to perform reaching movements with a virtual robotic arm controlled via limited head motion; thereby, employing unusual muscles and body segments, which mitigates influence from prior motor experiences (Card et al., 1991; Casadio et al., 2012; Mussa-Ivaldi et al., 2011; Shuggi et al. 2017, 2018, 2019). In particular, this experimental platform requires individuals to first acquire the mapping between head motion and the end-effector of the robotic arm (this corresponds to the first specific aim). Then, once this has been completed, the robotic controller can be manipulated at will to act as a synthetic partner to examine human cognitive-psycho-motor performance in a team context (this corresponds to the second specific aim).

Due to successful use of this particular HMI paradigm in prior behavioral research related to motor practice, it was decided to integrate EEG with this system (Shuggi et al., 2017, 2018, 2019). Hence, in order to accurately measure cortical dynamics when individuals perform a reaching task with such a head-controlled system, a de-noising algorithm to remove head motion artifact from the EEG signals was implemented based on prior work (Daly et al., 2013; Kim et al., 2015; Onikura et al., 2015; see methods section for details).

Therefore, the first study of this dissertation aimed to assess the feasibility of using EEG with this experimental platform in order to investigate the simultaneous changes in attentional reserve and cognitive-motor effort. As previously mentioned, such a combined assessment could provide a robust collective index of mental workload dynamics accompanied with changes in motor performance throughout practice. In particular, it was hypothesized that, as participants progressed through practice, performance would improve. Additionally, attentional reserve would increase (i.e., increase in novelty-P3 amplitude) and cognitive-motor effort would decrease (i.e., increases in low-/high-alpha power), which would collectively indicate an attenuation of mental workload.

Then, as an extension to the first study, the second study aimed to introduce a synthetic teammate to perform with the human partner, who was already trained to perform the reaching task with the HMI. The introduction of the synthetic teammate allowed for assessment of the relationship between cognitive-psycho-motor performance and psychological factors (e.g., self/collective efficacy and trust) while manipulating interdependence. The type of dependence was varied from unilateral (one teammate is more dependent) to mutual (teammates are equally dependent), by directly altering the task interdependence from reciprocal to team (Jackson et al., 2010; Saavedra et al., 1993). Specifically, we considered i) a reciprocal condition where the human user is less dependent on the robot (H-r), ii) a reciprocal condition where the human user is more dependent on the robot (h-R), and iii) a team condition where the human and robot are equally dependent (h-r). Here the robot acted as a helper to facilitate task performance. It was predicted that, the H-r, h-r and h-R conditions will result in a: i) low, moderate and high level of motor performance, ii) moderate, high and low level of mental workload, iii) high, moderate and low level of self-efficacy, respectively. Both collective efficacy and trust of the H-r and the h-R conditions were expected to be comparable and higher than that of the h-r condition, due to belief in personal ability as well as belief in the ability of the robot.

Chapter 2: Study I Methods – combined assessment of mental workload throughout practice

2.1 Participants

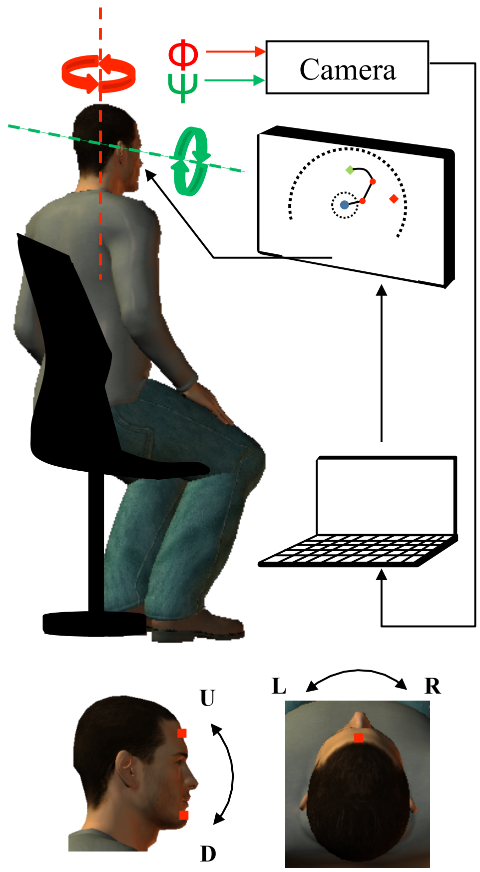
Twenty participants from the University of Maryland and surrounding Washington, DC area enrolled in this study[1]. Due to excessive noise in the EEG data, one participant was removed so the final sample included nineteen participants (8 males and 11 females, age ranged between 18 and 35 years old). Hence, the gender and race of the study population is reflective of the demographics of the university and surrounding area. The inclusion criteria for the participants were to be right handed, which was determined by the Edinburgh Handedness Inventory questionnaire (Oldfield, 1971), free from any known neurological disorders and between the ages of 18 and 35. Furthermore, participants did not have any significant experience with video games, on average not playing more than 4 hours per week within the last year and specifically, no experience with head motion controlled systems. Participants who reported use of alcohol, nicotine, or psychotropic drugs within the 24 hours of testing were excluded. All participants provided informed consent prior to involvement in the study.

2.2 Experimental Platform

Both studies presented here employ the same HMI, which uses a visuomotor reaching task. Specifically, participants controlled a two-degree of freedom virtual robotic arm with limited head motion to perform reaching movements. A motion

[1] Twenty-four people were enrolled; however, two did not complete the study, technical issues affected another participant's data collection and one participant did not sign the consent form.

capture system (Optotrak™) captured the real time displacement of an infrared sensor, placed on the participant's forehead. A basic decoding algorithm converted the displacements of the sensor into the corresponding movements of the virtual robotic end-effector within a two-dimensional workspace.



$$(\Phi,\Psi) = \boldsymbol{f}^{-1}\,(X,Y)$$

Figure 3: HMI as experimental platform and corresponding signal processing. The subject must learn a simple sensorimotor mapping ($f^{\,1}$) between angular head movements (pitch: Ψ and yaw: ϕ) and the spatial displacements (X and Y) of the end-effector.

Participants were seated approximately 60cm from a screen, which displayed the robotic end-effector and workspace. During a brief calibration phase participants determined the limits of their range of motion. Limited angular head rotations (yaw and pitch), allowed the participants to control the displacements of the virtual robotic end-effector through a closed loop inverse kinematic algorithm. Specifically, participants could move their heads in eight directions: up, down, left, right and diagonally. This head-control mechanism is similar to joystick control, when a participant's head was in the center of the defined range then the end-effector remained stationary. Once a participant turned his or her head beyond a specified threshold then the end-effector moved at a velocity proportional to the magnitude of the participant's head rotational displacement.

Red targets appeared randomly throughout the workspace, one at a time. Target acquisition occurred after the participant held his or her head in a central position for at least two seconds to provide enough time to plan their movement (i.e., planning stage). If the participant moved his or head prior to the two-second requirement, the target turned black until the participant moved his or her head back into the central position. After a target was acquired it turned green, then participants could move their heads in the desired direction to reach the target as fast and as straight as possible while avoiding collisions with the boundaries (i.e., execution stage). Once the target was reached the participant was required to hold the end-effector over the target for two seconds before it disappeared and the next target appeared. The inner boundary surrounded the base of the robotic end-effector (i.e., the shoulder), while the outer boundary enclosed the workspace. A customized MATLAB™ program was used for the implementation of this HMI, to send triggers to an EEG system to mark the planning and execution periods of reaching movements for each trial, to implement the synthetic teammate, and collect the behavioral data.

This experimental platform was employed, since it provided an opportunity for participants to perform a novel and challenging task. Specifically, neck muscles are not commonly used for fine control such as the control needed to move the virtual robotic end-effector as fast and as straight as possible throughout the two-dimensional workspace. Such a unique use of the neck muscles mitigates biases from previous motor experiences (Casadio et al., 2012; Mussa-Ivaldi et al., 2011). Additionally, neck muscles have a reduced number of communication channels, which creates a challenge when attempting to perform precise motor movements (Jagacinski & Monk, 1985; Card et al., 1991). Prior efforts have revealed that this platform was able to successfully i) examine cognitive motor control and learning and ii) generate conditions where there is a particular need for a partner (Shuggi et al. 2017, 2018, 2019).

2.3 Experimental Design

In order to address the first specific aim, the first study recorded changes in cortical dynamics via EEG and kinematics of the virtual robotic arm throughout the practice session. Prior to completion of the practice session, participants completed a brief familiarization phase to become acclimated with the necessary head motions. Participants were instructed to move the virtual robotic arm as fast and as straight as possible before starting the practice session. The practice session consisted of 200 equally distanced trials (5 blocks of 40 trials), which prior work has shown was sufficient to see improved performance (Shuggi et al., 2017, 2018, 2019). Participants completed this practice session without any assistance (i.e., they fully controlled the virtual robotic effector).

2.4 <u>Data collection and processing</u>

The first two sections provide details regarding kinematic data collection and processing (section 2.4.1) as well as EEG data acquisition (section 2.4.2). The last two sections describe EEG processing in the context of artifact removal (section 2.4.3) and mental workload assessment (section 2.4.4).

2.4.1 Assessment of kinematic performance

2.4.1.1 Performance metrics

Due to use of the same visuomotor reaching task in both experiments, it is important to note that performance was assessed through the same kinematics of the virtual robotic end-effector. In particular, six metrics were used: i) the number of control signals (CS) sent to the end-effector, defined as the number of times a head movement sent a command to the end-effector to move in a specified direction, ii) movement time (MT), defined as the time elapsed between two sequential targets, iii) movement length (ML), defined as the distance travelled between two consecutive targets, iv) normalized jerk (NJ), a quantification of movement smoothness, defined as the absolute jerk while accounting for movement time and path length of the end-effector (Kitazawa et al., 1993), v) throughput (TP), which measures the amount of information a participant sends through a command source (Williams & Kirsch, 2008, 2015), and vi) path efficiency, a quantification of the straightness of the trajectory, is defined as the ratio between the ideal shortest distance over the actual distance traveled by the end-effector (Lau & O'Leary, 1993; Williams & Kirsch, 2008, 2015). All of these kinematic measures were employed to assess cognitive-motor performance in previous studies in which the head-controlled platform described above was employed (Shuggi et al., 2017, 2018, 2019).

Although these prior efforts examined human cognitive-motor processes by means of behavioral metrics (e.g., kinematics, surveys), they did not incorporate EEG, which can provide insight into changes in cortical dynamics throughout testing. In the two studies presented here, in addition to the collection of behavioral data, EEG was integrated into this platform thereby increasing our understanding of the examined cognitive-motor processes. It must be noted, that the addition of EEG to this head controlled platform represented a critical technical challenge. Specifically, head motion artifact must be removed from the EEG data prior to the derivation of relevant cortical biomarkers to examine cognitive-motor processes. Hence in the first study, the implementation of such a de-noising method was a prerequisite to the examination of changes in mental workload through the combined assessment of attentional reserve and cognitive-motor effort during practice.

2.4.1.2 Statistical analysis

All kinematic metrics were assessed by a paired *t*-test, comparing the early (first 50) and late (last 50) trials of performance, unless normality was violated in which case a Wilcoxon signed rank test was used. Cohen's d effect sizes are provided when appropriate. The alpha significance threshold was set to $p < 0.05$.

2.4.2 Electrophysiological data acquisition

While participants performed the reaching task, a 64-electrode EEG cap was used to collect EEG data, sampled at a rate of 1000Hz. An inertial measurement unit (IMU; Xsens™) was employed for tracking the angular rotations of the participants' head movements. In particular, the IMU captured the acceleration and angular velocity of head motion sampled at 100Hz. After the EEG cap was placed on the participant's head and gelling was complete, the IMU was placed on the front of the participant's head. The IMU data was used to remove head motion artifacts from the EEG data (figure 5).

Throughout the practice session, participants were probed with a set of 30 task-irrelevant auditory stimuli (Dyke et al. 2015; Miller et al., 2011; Rietschel et al. 2014). These auditory stimuli were obtained from a larger collection from the New York State Psychiatric Institute (Fabiani et al., 1996). Once participants initiated movement towards the required target, a sound was randomly played before they reached the target. Triggers were used to mark the EEG data in order to identify when: i) a target appeared, ii) movement onset occurred, iii) a sound was played and iv) a target was reached (figure 4).

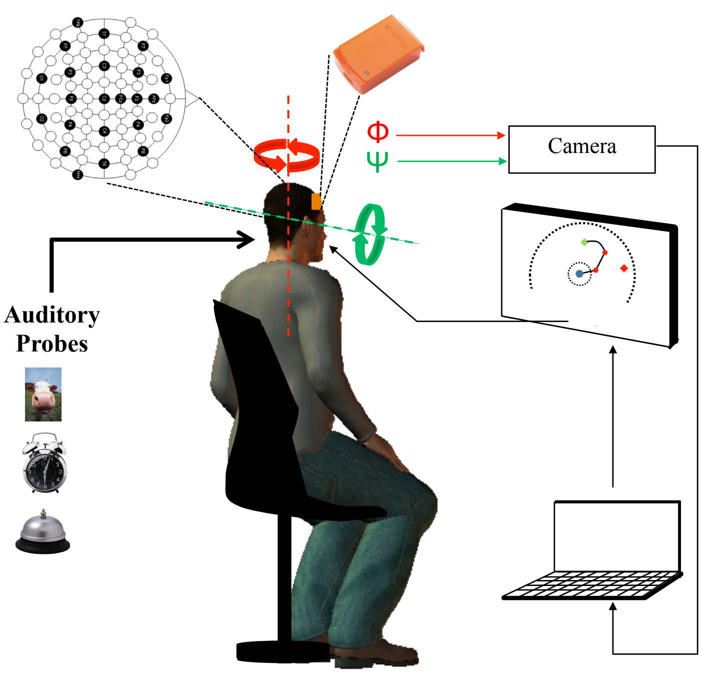


Figure 4: Experimental platform with EEG and IMU incorporated. EEG was collected throughout testing to assess attentional reserve and cognitive-motor effort. Sounds were played throughout the session in order to evaluate attentional reserve.

2.4.3 Electrophysiological data processing: removing head motion artifacts

As previously mentioned, a de-noising method was implemented for head motion removal, which allowed for more accurate derivation of EEG metrics needed to investigate mental workload changes via a combined assessment of attentional reserve and cognitive-motor effort during practice. It must be noted that while EEG analysis was conducted during both the planning and execution stages of the reaching movement, head motion artifact removal was particularly critical for the latter since no body movement occurred during the former. In order to assess the performance of the developed de-noising method and due to the complexity of removing head motion artifact from the EEG data, three methods were used to complete a spectral analysis (section 2.4.3.5) and two methods were employed to complete an event-related potential (ERP) analysis of the data (section 2.4.4.2). The following sections detail the implementation of these methods.

2.4.3.1 Method 1: Traditional EEG processing

One method, which was used to process the EEG data, is considered to be a more traditional method of cleaning using BrainVision Analyzer. The EEG data were first re-referenced to an averaged ears montage. Then data were band-pass filtered between 2 and 50Hz with a 48-dB rolloff and notch filtered at 60Hz using a zero-phase shift Butterworth filter. Next a pruning technique was employed and then an ocular-based independent component analysis (ICA) was employed to identify artifacts. Specifically, eye artifact was reduced using an artifact rejection function embedded in the software. Identified components were removed and then the data were baseline corrected on the entire practice session. The data were then down sampled to 500Hz to allow for comparison across all processing methods. Artifact rejection on a trial-by-trial basis was implemented using Cook's distance (Khatun et al., 2018). Specifically, for each participant a linear model was fit to each frequency band (theta, low-/high-alpha as well as low-/high beta). Cook's distance was then applied to determine if any trials were influential on each model. Trials with a distance greater than 1 were considered as influential on the linear model (Cook & Weisberg, 1982). None of the subjects had trials with a Cook's distance greater than 1, thus no trials were excluded.

2.4.3.2 Method 2: Eye blink removal

Similarly to the traditional method, the first step of this method was also to re-reference the data to an averaged ears montage. The data was then band-pass filtered between 3 and 40Hz with an eighth-order Butterworth filter. The EEG signal was then down sampled to 500Hz, once again to create comparable datasets. A second-order blind identification (SOBI) ICA was then applied to identify artifacts within the EEG data, with the objective of primarily removing ocular artifacts.

2.4.3.3 Method 3: Head motion artifact de-noising algorithm (HMAD)

The following de-noising algorithm was built upon other head motion artifact algorithms (Daly et al., 2013; Kim et al., 2015; Onikura et al., 2015). The EEG and IMU data were analyzed separately before computing the cross correlation between the two signals, in order to identify head motion artifacts within the EEG signal. The EEG data were analyzed using EEGLAB. After re-referencing the data to an averaged ears montage, an eighth-order Butterworth filter was used to band-pass filter the data between 3 and 40Hz. The EEG signal was then down sampled to 500Hz in order to calculate the cross correlation with the IMU data.

In addition to the acceleration and angular velocity recorded by the IMU, the velocity and angular acceleration of the head motion were also calculated. These calculations increased the amount of information related to the participants' head motion, which improved our ability to identify independent components in the EEG data related to head motion artifact. The IMU data were processed in EEGLAB, by first using an eighth order Butterworth filter to band-pass the data between 1-10Hz. The IMU signal was then up sampled to 500Hz. A SOBI ICA was completed for both the EEG and IMU data in order to decompose the signals into individual components, which could be used for the cross correlation calculation.

After calculating the independent components of each dataset, the cross correlation was calculated based on the assumption that the there is a +/-10ms lag between the EEG signal and IMU signal during data collection. This is based on the programming of triggers during data collection of both signals. After identifying the correlated components from the EEG ICA and the IMU ICA, these components were removed and the EEG signal was reconstructed. After removing all components correlated with the head motion, any possible eye artifact was also removed. Lastly, the remaining components were considered based on their power spectrums and variance (see figure 5).

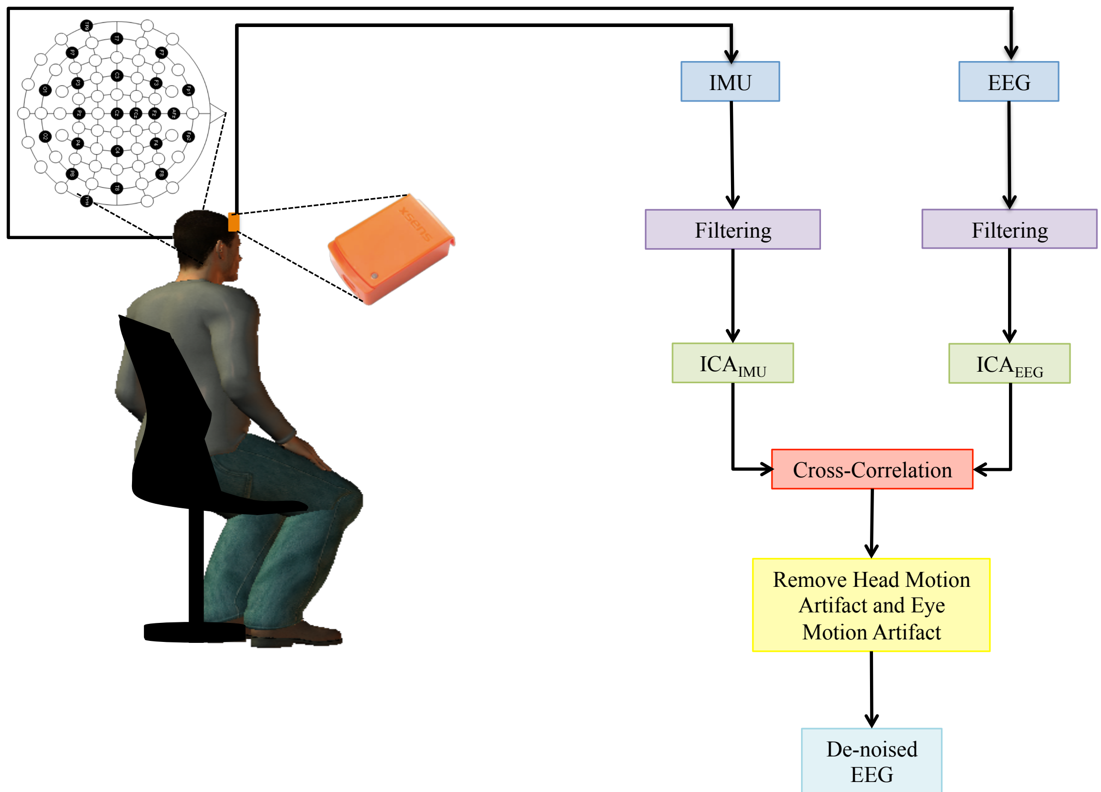


Figure 5: Proposed method to remove head motion artifacts from EEG signal. Left: The subject wears a 64-channel EEG cap and the IMU is placed on the front of the head. Right: Procedure for de-noising EEG signal.

2.4.3.4 Spectral comparison of de-noising methods

Assessment of these de-noising techniques was based on approaches employed in previous studies that have proposed similar head motion artifact removal techniques (Daly et al., 2013; Onikura et al., 2015). A comparison of the spectral power for various frequency bands and cortical regions when the EEG was contaminated by head motion (i.e., execution stage; defined from movement onset to target reach) was considered. Namely, several frequency bands of interest that have been traditionally employed in prior cognitive-motor studies were examined. In particular, the spectral power analysis was calculated across 0.5-Hz bins and averaged across the following frequency bandwidths: theta (4-7Hz), low alpha (8-10Hz), high alpha (11-13Hz), low beta (14-22Hz) and high beta (23-35Hz) (Gevins & Smith, 2003; Moisello et al., 2015; Rietschel et al., 2012; Shaw et al., 2018). The theta and high-beta frequency ranges were of particular interest since they are mainly related to head motion and EMG, respectively.

In order to properly compare each of the aforementioned methods, a comparison analysis of each method to an established baseline was performed. Spectral power across the previously mentioned frequency bandwidths was calculated for data, which had only been re-referenced using the averaged ears montage. This was done to create a baseline at the only point where each spectral analysis method overlaps. Each method's power spectral values were then subtracted from the re-referenced data to evaluate the relative difference in power of each frequency band for each method. This relative difference can illustrate the impact of artifact removal from each method. In particular, examination of the relative difference allowed us to identify which frequency bandwidths and regions had the greatest reductions in spectral power.

The comparison between these three methods was statistically conducted by means of a 3 Method (Method 1, Method 2, Method 3) x 5 Region (frontal, central, temporal, parietal, occipital) repeated measures ANOVA. Post-hoc analyses were conducted by employing the Tukey's HSD test when necessary. If the sphericity assumption was not met, then the Greenhouse-Geisser was applied (in this case the p-values reported are associated with the corrected degrees of freedom). Partial eta squared and Cohen's d effect sizes are provided when appropriate. The alpha significance threshold was set to $p < 0.05$. Due to the lack of significant difference between methods 1 and 2, only methods 2 and 3 were used for further analysis[2] (for details of the performance of the EEG de-noising algorithms, see results section 4.2).

2.4.4 Electrophysiological data processing: mental workload assessment during practice

2.4.4.1 Spectral Analysis

Once the EEG data were de-noised by applying each processing method, a spectral power density analysis was performed, with a particular focus on the theta and alpha frequency bands. It has been shown that both theta and alpha are related to attention and allocation of cortical resources (Gevins et al., 1997). Specifically, an increase in task difficulty is reflected by an increase in theta and increases in frontal midline theta have been related to focused attention (Gevins et al., 1997; Ishii et al., 2014). Lower levels of low-alpha indicate high levels of general arousal and decreases in high-alpha indicate increased task related cortical activation (Gevins et al., 1997; Miller et al., 2014; Rietschel et al., 2012). Furthermore, task effects on alpha are generally more prominent over the parietal regions in comparison to the frontal regions (Gevins & Smith, 2000; Rietschel et al., 2012). Although head artifact removal from EEG was critical for the execution stage, in order to further assess the de-noising method presented here as well as be consistent with analyses of the cognitive-motor processes underlying practice of reaching movements, the EEG data were epoched around movement onset to consider both movement planning (early planning: -2 to -1 sec; late planning: -1 to 0 sec) and execution (from 0 sec to the time

[2] Method 2 was chosen over method 1 due to overlaps between method 2 and method 3. Specifically, method 2 and 3 were both bandwidth filtered into the same range (3 – 40Hz) and both methods employed a SOBI ICA.

elapsed to reach the target). Then, for each movement planning and execution stage, spectral power was calculated across 0.5-Hz bins and averaged across the following frequency bandwidths: theta (4-7Hz), low-alpha (8-10Hz), high-alpha (11-13Hz), low-beta (14-22Hz) and high-beta (23-35Hz) (Gevins & Smith, 2003; Moisello et al., 2015; Rietschel et al., 2012; Shaw et al., 2018). Analyses of low and high-beta were exploratory. Spectral power values were natural log transformed prior to statistical analysis.

2.4.4.2 Event-Related Potential (ERP) Processing

In addition to the spectral power density analyses, data processing methods 2 and 3 were applied for the event-related potential (ERP) analyses to assess cognitive resource allocation (Miller et al., 2011, 2014). These two separate analyses were performed to evaluate the impact of head motion artifact on ERPs. Both analyses were focused on the examination of the P300 component since it has been associated with the amount of cognitive resources used to process a stimulus (Luck, 2014). Specifically, the P3a (or novelty-P3) component has been shown to be related to attention directed towards a stimulus during task processing (frontal, 220-280ms), while the P3b is related to attention, but more specifically memory processing (temporal-parietal, 310-380ms; Barry et al., 2016; Polich, 2007). It has also been shown that an increase in task difficulty, leads to a decrease in the amplitude of the P300 component (Rietschel et al., 2014; Miller et al., 2011; Polich, 2007).

As previously mentioned, both methods required re-referencing of the data to an averaged ears montage, followed by filtering the data with an eighth-order Butterworth filter between 3 and 40Hz. Additionally, a SOBI ICA was applied in both methods. At this point, the two methods diverged (i.e., method 2 primarily removed ocular artifact and method 3 removed ocular and head motion artifact), and did not re-align until the data was divided into one-second epochs of non-overlapping windows, time-locked to the auditory stimuli (-100ms pre-stimulus and 900ms after the stimulus). The data were then baseline corrected using the mean of the pre-stimulus interval and visually inspected for additional artifacts. The remaining epochs of each participant, across the entire practice session were averaged in order to compute the grand average waveform for the following sensors Fz, FCz, Cz, and Pz. The grand average waveform was then used to identify the appropriate window based on the peak amplitude; lastly the mean amplitude was extracted for each participant's set of trials. Mean amplitudes were extracted using a 40ms time window for both methods. For the method, which primarily removed eye blinks (method 2), the identified time window for the novelty-P3 was 220-260ms and for the method, which removed head motion artifact (method 3), the identified time was 246-286ms.

***2.4.4.3* Statistical Analysis**

To assess the changes in spectral content during practice, a series of 2 Period (early, late) x 2 Hemisphere (left, right) x 5 Region (frontal, central, temporal, parietal, occipital) repeated measures ANOVA were conducted. In addition, the changes of mean amplitudes of the novelty-P3 component were subjected to a 2 Period (early, late) x 4 Region (Fz, FCz, Cz, Pz) repeated measures ANOVA. For all analyses, post-hoc analyses were conducted by employing the Tukey's HSD test when necessary. If the sphericity assumption was not met, then the Greenhouse-Geisser was applied (in this case the *p*-values reported are associated with the corrected degrees of freedom). Partial eta squared and Cohen's d effect sizes are provided when appropriate. The alpha significance threshold was set to $p < 0.05$.

Chapter 3: Study II Methods – influence of interdependence on cognitive-psycho-motor processes during team performance

3.1 Participants

Twenty-one participants enrolled in the second experiment (7 males and 14 females, age ranged between 18 and 35 years old)[3]. The participant selection criteria were the same as for study 1. However, contrary to study 1, participants received $50 for completion of the study. The kinesiology department provided funding through the Graduate Research Initiative Project.

3.2 Experimental platform

In this study the same experimental platform was employed as for study 1 (please see section 2.2 for details).

3.3 Experimental design

In order to address the second specific aim, the first day of testing was similar to experiment one; however, there was the addition of a post-test, which included 20 trials from the practice session. After participants completed the post-test, they completed the NASA TLX survey in order to assess mental workload during the post-test.

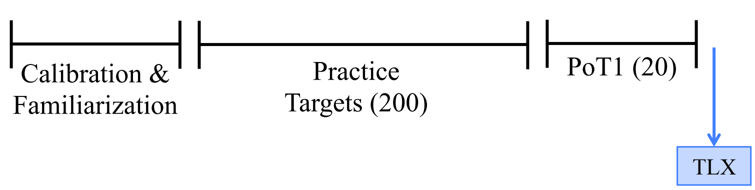


Figure 6: Timeline for first day of testing of the second experiment. After participants completed the practice session they took a brief break and then completed the post-test (PoT1). TLX: NASA TLX.

[3] Twenty-six people were enrolled; however, three did not complete the study and two were not included due to not following instructions.

The second day of testing occurred approximately 72 hours after the first day. After completing another brief familiarization, participants completed the same post-test they had completed on the first day of testing in order to evaluate the participant's retention (Kantak & Winstein, 2012). Specifically, the retention test assessed the stability of the human user's performance before being partnered with the synthetic partner. For the remainder of testing, participants completed the reaching task with a synthetic teammate during three different interdependence conditions, which were counterbalanced (see figure 7).

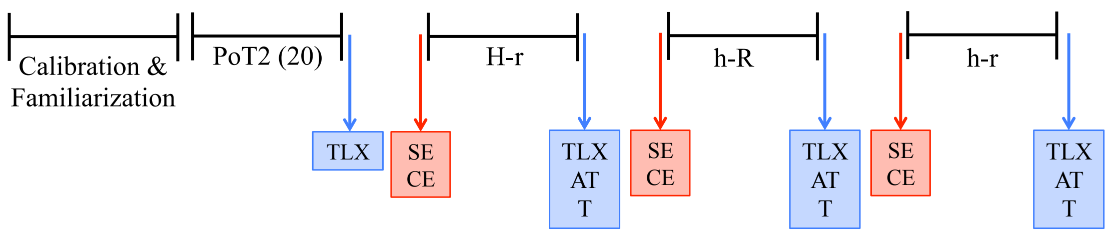


Figure 7: Timeline for second day of testing of the second experiment. Blue boxes represent surveys, which were given after a condition and red boxes represent surveys given before a condition. TLX: NASA TLX, SE: Self-efficacy, CE: Collective efficacy, AT: Attribution, T: Trust.

Two types of dependence were tested: i) unilateral dependence, where one teammate is more dependent of its partner and ii) mutual dependence, where the teammates are equally dependent (Jackson et al., 2010). Variations in dependence were implemented through a manipulation of task interdependence (Saavedra et al., 1993). As previously mentioned, the level of task interdependence was manipulated as follows: i) a reciprocal condition where the human user was less dependent on the robot (H-r), ii) a reciprocal condition where the human user was more dependent on the robot (h-R), and iii) a team condition where the human and robot were equally dependent (h-r). Within the H-r condition the human was responsible for the majority of the required actions (target selection and movement), while the synthetic teammate had the reduced role of accurately completing the reach (figure 8, panel A). The h-R condition was the opposite, with the teammate assigned greater responsibility than the human; specifically, the human was primarily responsible for target selection (figure 8, panel B). Lastly, in the h-r condition the human and synthetic teammate shared responsibility of the end-effector's movement; the human was responsible for target selection and the teammate assisted with the accuracy of the reach (figure 8, panel C).

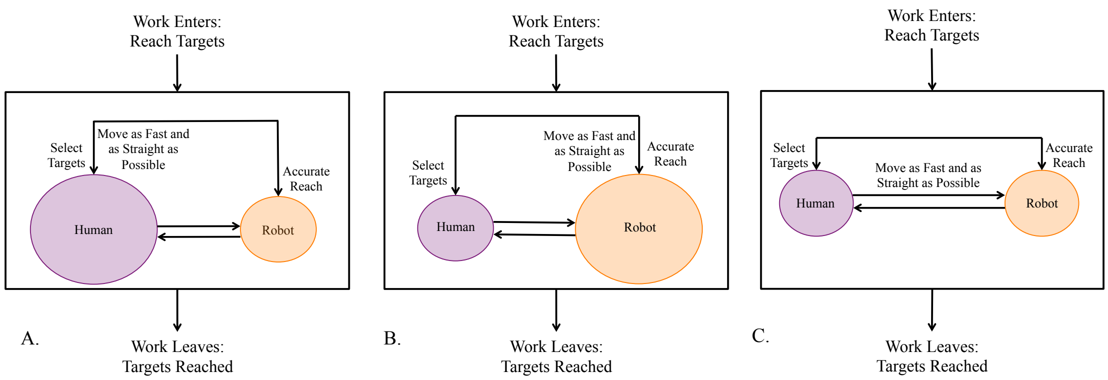


Figure 8: There were three different experimental conditions to address the second specific aim. (A) The human user was less dependent on the synthetic partner (reciprocal; H-r); (B) the human user was more dependent on the synthetic partner (reciprocal; h-R); (C) the human user and synthetic partner are mutually dependent (team; h-r). (Adapted from Saavedra et al., 1993; Van de Ven et al., 1976).

The three different types of task interdependence were implemented through a blending method developed by Goil and colleagues (2013). The synthetic partner's velocity and direction were based on the recurrent error-driven adaptive control hierarchy (REACH) model from DeWolf and colleagues (2016). The synthetic partner's velocity and direction were blended with the user's velocity and direction, by the following equation:

$$T = (1 - \beta)R + \beta H$$

where β is the blending coefficient, T is the blended team movement, R is the robot's movement, and H is the user's movement. The blending coefficient is calculated as:

$$\beta = \exp(-\Delta v/\sigma)$$

where $\Delta v = |H - R|$. The main premise of this method is the dependence on the variance (σ). When the variance is zero, the blending coefficient β is zero indicating that full control is being given to the synthetic partner. Conversely, when β is one then the user would have complete control. Hence, the variance between the user's velocity and the robot's velocity were manually manipulated to create the three levels of interdependence. Specifically, the blending coefficient was set to have the following manipulations: majority control by the human user ($\beta = 0.9$), majority control by the synthetic teammate ($\beta = 0.1$) and shared control ($\beta = 0.5$).

3.4 Data collection and processing

The first section provides details about surveys used throughout the experiment (section 3.4.1), followed by information about kinematic performance (section 3.4.2). Details regarding EEG data acquisition and processing (section 3.4.3) are then provided followed by methods used for statistical analysis (section 3.4.4).

3.4.1 Surveys

3.4.1.1 Mental Workload

Mental workload was assessed by the NASA TLX survey, which has been validated for reporting perceptions of workload in many different areas of research including cognitive and psychomotor performance, piloting, and medical procedures as well as while examining cognitive-motor performance with this platform (Ayaz et al., 2013; Gentili et al., 2014; JS Hu et al., 2016; Hart & Staveland, 1988; Hart, 2006; Miller et al., 2011; Shuggi et al., 2017, 2018, 2019; Zheng et al., 2012). While the NASA TLX is a subjective assessment of perceived workload, it has provided results that are consistent with more objective measures such as those derived from EEG (e.g., Gentili et al., 2014; Ke et al., 2014). The NASA TLX is made up of six dimensions, which are thought to provide an overall index of workload: mental, physical, and temporal task demands as well as effort, frustration, and perceived performance. In particular, the mental demand dimension has been reported to most likely correspond with mental effort (Akizuki & Ohashi, 2015; Ayaz et al., 2013; Hart, 2006; Van Gog & Paas, 2008); thus, there was a particular focus on mental demand. Participants completed the NASA TLX after each of the post-tests (on day one and two), as well as after every testing conditioning on day two.

3.4.1.2 Efficacy

The self-efficacy and collective efficacy surveys followed the guidelines established by Bandura (1997, 2006). Both surveys used 11-point Likert scales (0 to 100) and addressed three components of the reaching task: i) reaching the targets as fast as possible, ii) reaching the targets as straight as possible, and iii) overall performance of the task. The second day of testing included the self-efficacy as well as the collective efficacy survey before each condition. The difference between the self and collective efficacy survey were the stems. Specifically, the self-efficacy survey was only concerned with the individual's beliefs in his or her ability to complete the task, while the collective efficacy survey was concerned with the individual's belief in the abilities of the team.

3.4.1.3 Sense of Attribution

Based on the Causal Dimension Scale II (CDS-II) from McAuley and colleagues (1992), a modified CDS-II from Chow and Feltz (2008) as well as the Causal Dimension Scale for Teams (CDS-T) from Greenlees and colleagues (2005), a survey was developed to assess the participant's sense of attribution after each teammate condition. Specifically, there were six questions related to the locus of causality dimension and six questions concerned with personal/team control. Within each set of six questions for each of these dimensions, three questions were related to the person in comparison to their teammate and three questions were related to their team in comparison to an extraneous stimulus. Additionally, three questions focused on the dimension of external control and three questions focused on stability. Please see appendix E for more details. For statistical analysis, responses from questions related to each dimension were averaged together. Similar to the CDS-II, the modified CDS-II and the CDS-T, all questions had a 9-point response scale.

3.4.1.4 Trust

Trust was assessed using a survey adapted from de Visser and colleagues (2018), although they used a single question survey, we had a total of four questions. Three questions used the stem, "To what extent do you trust your teammate…" and addressed speed, accuracy and overall performance. The final question asked about overall trust in their teammate.

3.4.2 Assessment of kinematic performance

The same performance metrics from study 1 were employed (please see section 2.4.1 as well as Shuggi et al. 2017, 2018, 2019 for details).

3.4.3 Electrophysiological data acquisition and processing

In this second study, the same EEG acquisition approach was employed as for study 1. Namely, a 64-electrode EEG cap was used to collect EEG data, along with an IMU (Xsens™) to track head motion, which could be used to subsequently de-noise EEG signals by employing the previously described method (see section 2.4.3.3 for details). Similarly to the first study, participants were probed with irrelevant auditory stimuli as previously described and the same triggers were used to identify the same events (for details see section 2.4.2). Unfortunately, unexpected technical difficulties during the EEG data collection resulted in corrupted signals and as such cortical dynamics were not included in the rest of this document.

3.4.4 Statistical analysis

Paired *t*-tests were used to compare the results of the NASA TLX and kinematic measures between the post-test on day one (PoT1) and the post-test on day two (PoT2), unless normality was violated in which case a Wilcoxon signed rank test was used. A series of one-way repeated measure ANOVAs were conducted to analyze the surveys as well as the kinematic metrics from each teammate condition (H-r, h-r, h-R). If normality was violated then a log transform was applied; however, for clarity graphs do not show transformed values. Post-hoc analyses were conducted by employing the Tukey's HSD test when necessary. If the sphericity assumption was not met, then the Greenhouse-Geisser was applied (in this case the p-values reported are associated with the corrected degrees of freedom). Partial eta squared and Cohen's d effect sizes are provided when appropriate. The alpha significance threshold was set to $p < 0.05$.

Chapter 4: Study I Results – performance and mental workload throughout practice

The following sections present the results of the first study. Specifically, the kinematic metrics are presented (section 4.1) followed by an analysis of the methods used to de-noise the data (section 4.2). Lastly, the results of spectral power (section 4.3) and the novelty-P3 (section 4.4) in the context of practice are presented.

4.1 Practice kinematics

The statistical analysis of the kinematic parameters revealed an overall improvement in the performance of participants from early to late practice. Specifically, there was a significant decrease in the number of control signals used by the participants as they progressed throughout practice ($t(18) = 3.88$, $p = 0.001$, $d = 0.78$). There was also an attenuation of movement time as well as movement length (MT: $t(18) = 2.85$, $p = 0.011$, $d = 0.60$; ML: $t(18) = 2.91$, $p = 0.009$, $d = 0.69$). Furthermore, there was a decrease in normalized jerk from early to late practice ($Z = -2.18$, $p = 0.029$, $r = 0.50$). Lastly, participants significantly elevated their throughput as well as their path efficiency (TP: $t(18) = -3.91$, $p = 0.001$, $d = 0.81$; PE: $t(18) = -2.52$, $p = 0.021$, $d = 0.53$).

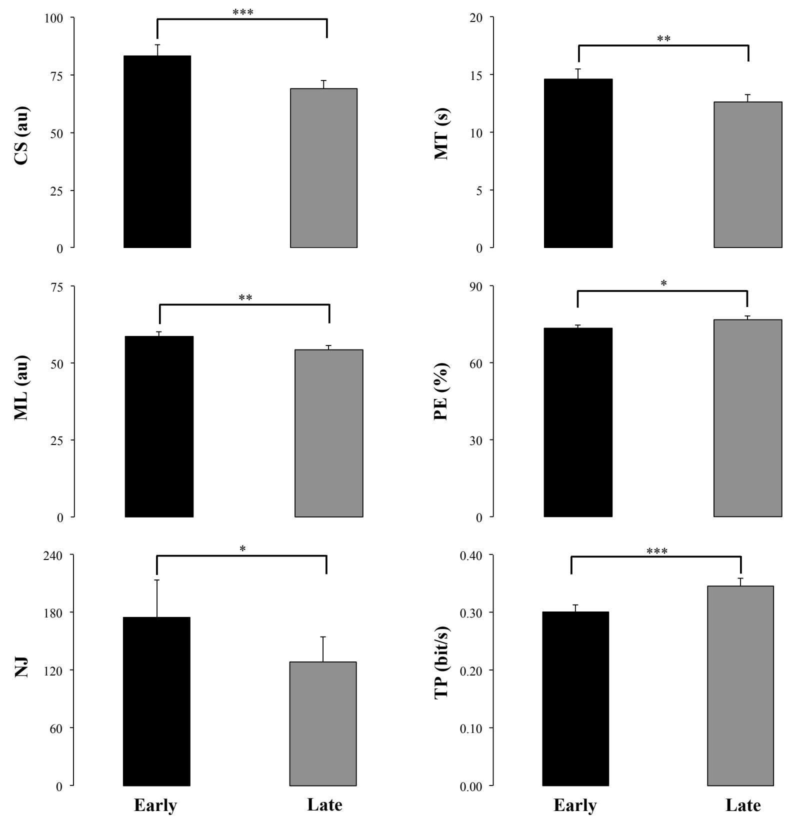


Figure 9: Kinematic performance during early to late practice. CS: number of control signals, MT: movement time, ML: movement length, PE: path efficiency, NJ: normalized jerk, TP: throughput. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

4.2 Spectral comparison of de-noising methods

For all frequency bands a significant main effect of Method ($p < 0.001$, $0.76 \leq \eta_P^2 \leq 0.88$)[4] was observed. There was a significant Method x Region interaction effect for theta ($F(2.47, 42.06) = 9.32$, $p = 0.002$, $\eta_P^2 = 0.35$), low-alpha ($F(2.38, 40.50) = 9.10$, $p = 0.003$, $\eta_P^2 = 0.35$), high-alpha ($F(2.26, 38.42) = 9.45$, $p = 0.003$, $\eta_P^2 = 0.36$) as well as low-beta ($F(1.94, 33.01) = 3.61$, $p = 0.003$, $\eta_P^2 = 0.18$). While post-hoc analyses revealed significant differences between methods 2 and 3, there were no significant differences between methods 1 and 2 for these frequency bands ($p > 0.05$).

[4] Due to technical issues with the IMU, one subject is missing for all EEG results associated method 3.

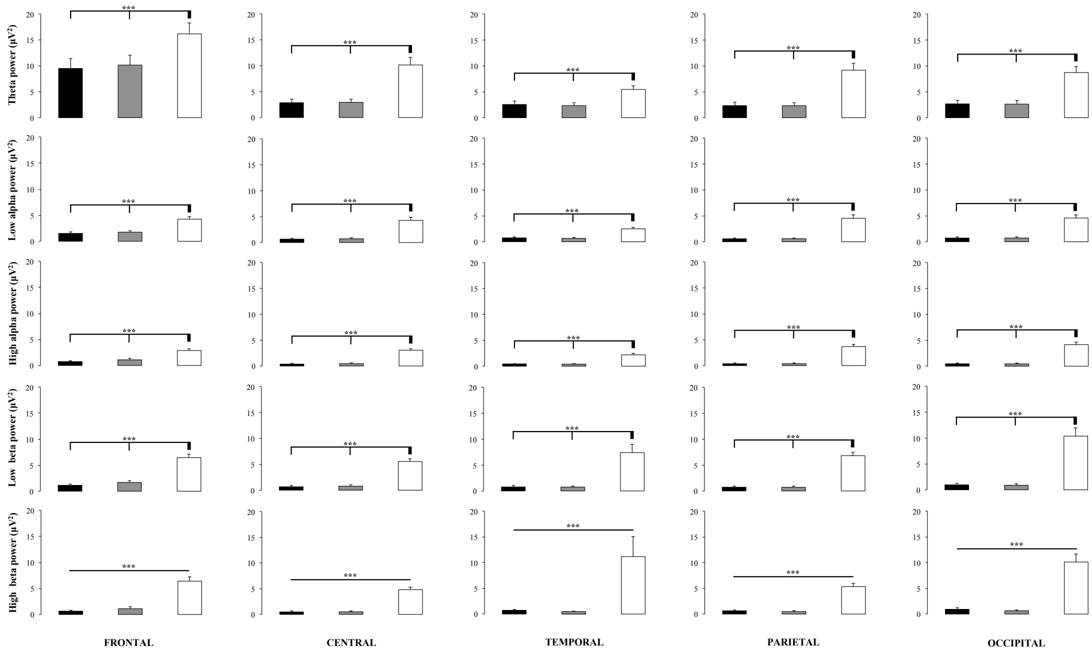


Figure 10: Comparison of spectral methods shown by frequency and region. The thick part of the fork represents the value, which is being used as a reference and compared to the other values (thin line; e.g. comparison between method 3 (thick line) vs. method 1 and 2 (thin lines)). ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Thus, in the rest of this document only the results for methods 2 and 3 are presented and later discussed. Please see appendix A for additional details on this statistical analysis. Figure 11 presents an additional comparison of methods 2 and 3 to further highlight differences.

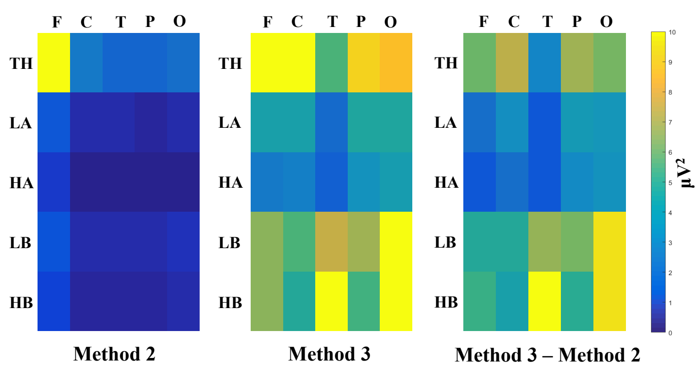


Figure 11: Comparison of reduction of spectral power after de-noising EEG with methods 2 (left panel) and 3 (middle panel) for all the relevant frequencies (TH: theta, LA: low-alpha, HA: high-alpha, LB: low-beta, HB: high-beta) and regions (F: frontal, C: central, T: temporal, P: parietal, O: occipital). For each method, warmer and cooler colors present increased and decreased power, respectively. The rightmost panel shows the contrast between method 3 and method 2.

4.3 <u>Cognitive-motor effort during practice</u>

The following sections present the results of the spectral analysis for methods 2 and 3. For each method the results for the early planning stage (-2 to -1 seconds before movement onset), late planning stage (-1 second before to movement onset) and execution (movement onset to target reach) are presented.

4.3.1 Early planning stage

4.3.1.1 Method 2

The statistical analysis revealed, a main effect of Period in low-alpha ($F(1, 18) = 38.08$, $p < 0.001$, $\eta_P^2 = 0.69$) as well as in high-alpha ($F(1, 18) = 11.74$, $p < 0.001$, $\eta_P^2 = 0.39$). Specifically, increases in both low and high-alpha were observed from early to late practice (see figure 12). Additionally, there was a Period x Region interaction for low-beta ($F(1.84, 33.08) = 6.61$, $p = 0.005$, $\eta_P^2 = 0.27$) and high-beta ($F(2.05, 36.92) = 6.03$, $p = 0.005$, $\eta_P^2 = 0.25$). Post-hoc analyses revealed an increase in the frontal region for low-beta ($p = 0.003$, $d = 0.43$) as well as a decrease in the temporal region for high-beta ($p = 0.003$, $d = 0.24$).

4.3.1.2 Method 3

For method 3, the findings revealed main effect of Period in low-alpha ($F(1, 17) = 19.68$, $p = 0.004$, $\eta_P^2 = 0.53$); specifically an increase in low-alpha from early to late practice, which is shown in figure 12. This main effect was superseded by a Period x Region interaction ($F(4, 68) = 4.09$, $p = 0.005$, $\eta_P^2 = 0.19$) as well as a Period x Hemisphere x Region interaction effect ($F(4, 68) = 2.73$, $p = 0.04$, $\eta_P^2 = 0.14$).

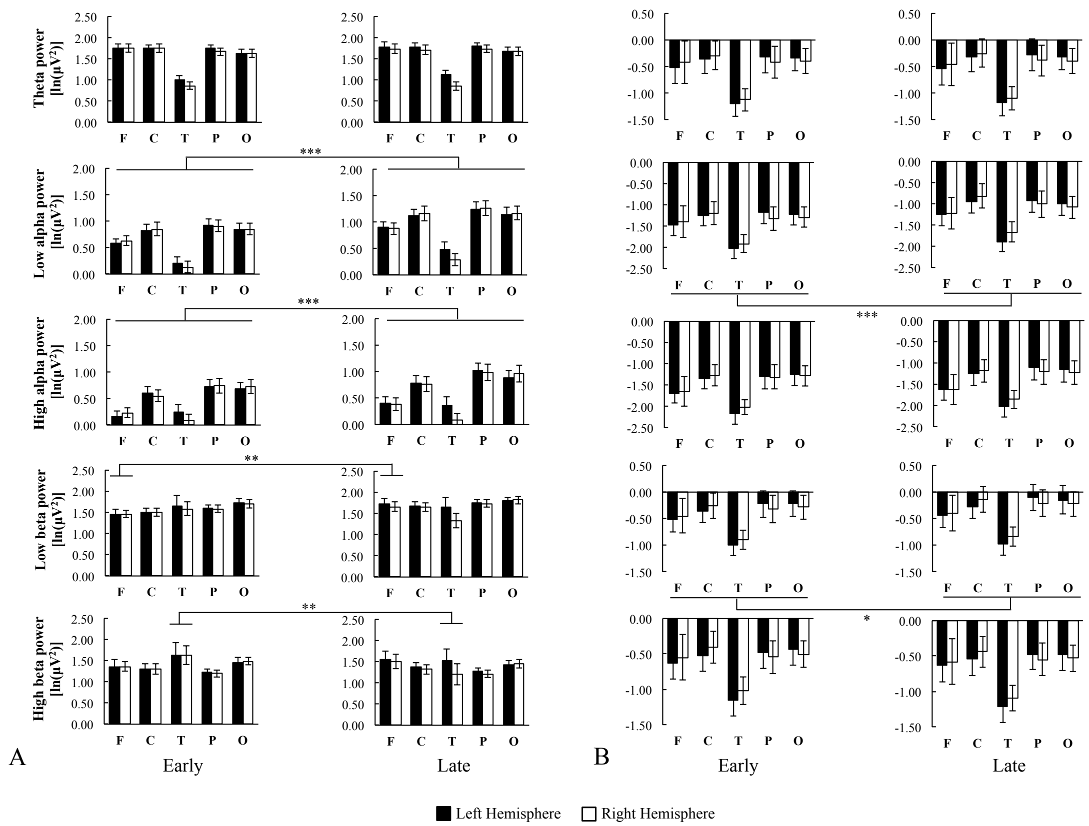


Figure 12: Early planning for method 2 (panel A) and method 3 (panel B) from early to late practice. Each panel shows, each region (F: frontal, C: central, T: temporal, P: parietal, O: occipital) and hemisphere (left: black bars, right: white bars) for theta, low alpha, high alpha, low beta and high beta. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Post-hoc analyses revealed significant increases in low-alpha for all cortical regions and both hemispheres ($p < 0.001$, $0.12 \leq d \leq 0.30$; for clarity these findings are not shown in figure 12). For low-beta, there was a main effect of Period ($F(1, 17) = 5.46$, $p = 0.032$, $\eta_P^2 = 0.24$) such that there was an increase from early to late practice.

4.3.2 Late planning stage

4.3.2.1 Method 2

For method 2, statistical analysis showed a main effect of Period for theta ($F(1, 18) = 10.54$, $p = 0.004$, $\eta_P^2 = 0.37$) such that there was an increase in theta power from early to late practice.

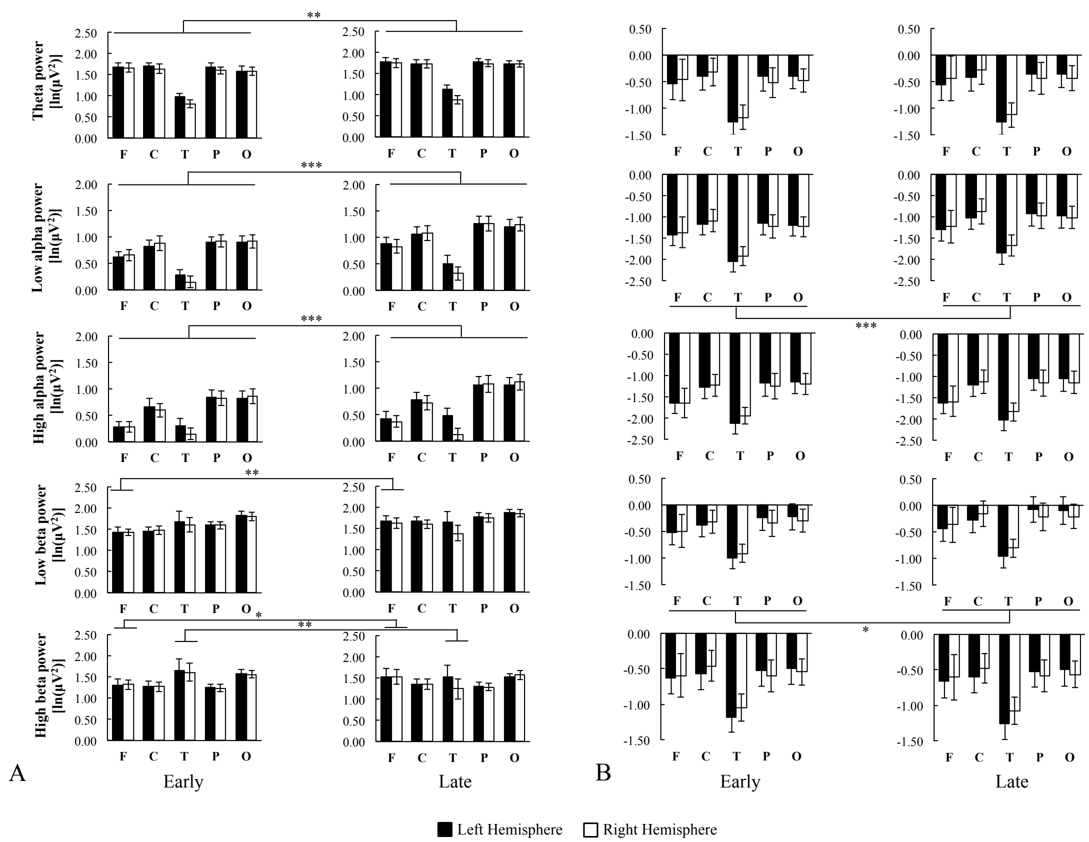


Figure 13: Late planning for methods 2 (panel A) and method 3 (panel B) from early to late practice. Each panel shows, each region (F: frontal, C: central, T: temporal, P: parietal, O: occipital) and hemisphere (left: black bars, right: white bars) for theta, low alpha, high alpha, low beta and high beta. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Additionally, a main effect of Period for both low-alpha ($F(1, 18) = 28.10$, $p < 0.001$, $\eta_P^2 = 0.61$) and high-alpha ($F(1, 18) = 7.89$, $p = 0.011$, $\eta_P^2 = 0.30$) was observed. For both low and high-alpha there were significant increases from early to late practice (see figure 13). There was a significant Period x Region interaction effect for both low-beta ($F(1.84, 33.13) = 6.41$, $p = 0.005$, $\eta_P^2 = 0.26$) and high-beta ($F(2.17, 39.12) = 7.16$, $p = 0.002$, $\eta_P^2 = 0.28$). Post-hoc analyses for low beta revealed an increase in the frontal region ($p = 0.004$, $d = 0.42$). The same analyses for high-beta showed an increase in high-beta in the frontal region ($p = 0.046$, $d = 0.29$) as well as a decrease in the temporal region ($p = 0.007$, $d = 0.28$).

4.3.2.2 Method 3

Statistical analysis revealed a significant main effect of Period in low-alpha ($F(1, 17) = 17.98$, $p = 0.001$, $\eta_P^2 = 0.51$) such that an elevation of low-alpha power from early to late practice was observed. Additionally, for low-beta a main effect of Period ($F(1, 17) = 6.16$, $p = 0.024$, $\eta_P^2 = 0.27$) such that beta synchrony was observed from early to late practice. This main effect was superseded by a Period x Hemisphere x Region interaction ($F(2.88, 49.04) = 2.88$, $p = 0.047$, $\eta_P^2 = 0.15$). Post-hoc analysis revealed an elevation of low-beta power for the frontal, central, parietal and occipital regions for both hemispheres as well as an increase in the right hemisphere of the temporal region ($p < 0.05$, $0.08 \leq d \leq 0.15$; for clarity only the main effect of Period is depicted for low-beta in figure 13).

4.3.3 Execution stage

4.3.3.1 Method 2

For the execution stage of method 2, a main effect of Period was observed for low alpha ($F(1, 18) = 6.49$, $p = 0.020$, $\eta_P^2 = 0.26$). Specifically, a significant increase in low-alpha from early to late practice was revealed (see figure 14). Additionally, Period x Region interaction effects were observed for low-beta ($F(1.97, 35.48) = 7.65$, $p = 0.002$, $\eta_P^2 = 0.30$) as well as high beta ($F(2.26, 40.73) = 7.93$, $p = 0.001$, η_P^2

= 0.31). Post-hoc analyses for low-beta revealed an increase in the frontal region (p = 0.02, d = 0.36) as well as a decrease in the temporal region (p = 0.049, d = 0.19). Post-hoc analysis of high beta showed an increase in the frontal region (p = 0.011, d = 0.36).

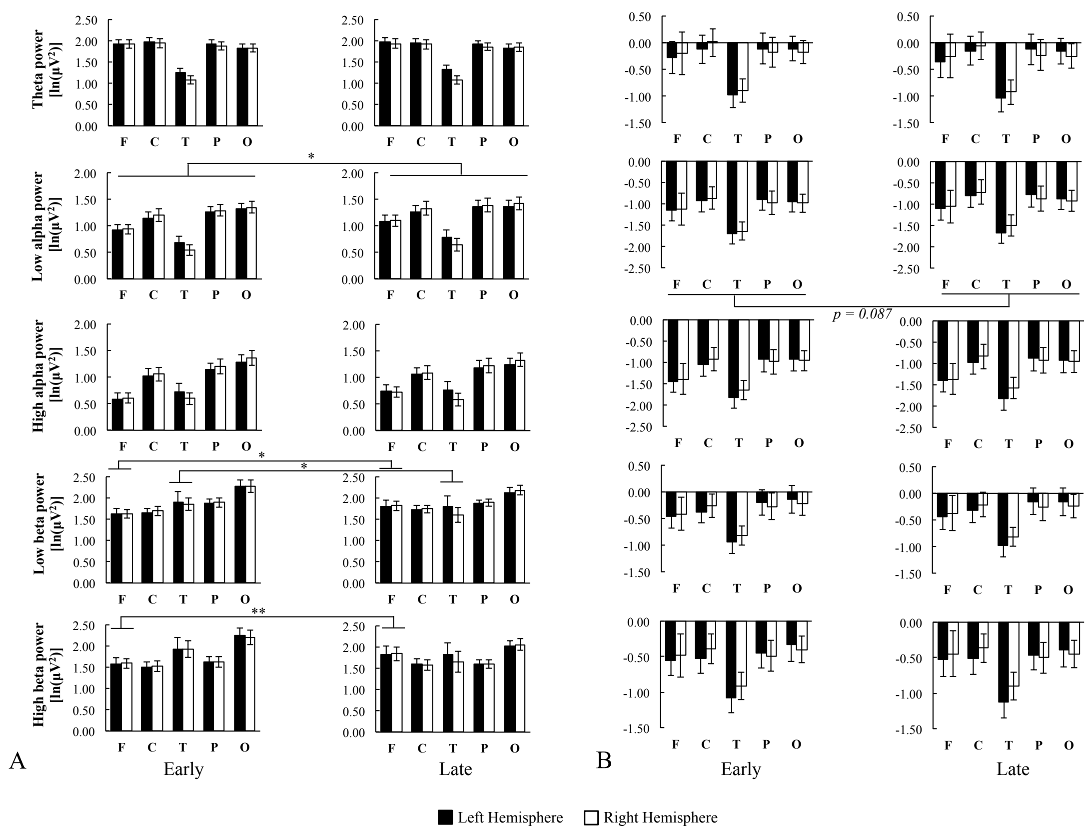


Figure 14: Cortical dynamics during the execution stage for method 2 (panel A) and method 3 (panel B) from early to late practice. Each panel shows, each region (F: frontal, C: central, T: temporal, P: parietal, O: occipital) and hemisphere (left: black bars, right: white bars) for theta, low alpha, high alpha, low beta and high beta. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

4.3.3.2 Method 3

The execution stage for method 3 did not reveal any significant results; however, there was a trend of significance showing an increase in low alpha from early to late practice ($F(1, 17) = 3.30$, $p = 0.087$, $\eta_P^2 = 0.16$). Additionally, there were trends of significance for Period x Region interaction effects for both low beta

($F(2.05, 34.89) = 2.68$, $p = 0.082$, $\eta_P^2 = 0.14$) as well as high beta ($F(2.44, 41.40) = 2.83$, $p = 0.06$, $\eta_P^2 = 0.14$).

4.4 Novelty-P3 throughout practice

Statistical analysis of the results provided by method 2 (which primarily removed eye blinks) did not reveal any significant differences for the novelty-P3 component amplitude. However, there was trend of significance revealing an increase in amplitude from early to late practice ($F(1, 9) = 3.56$, $p = 0.091$, $\eta_P^2 = 0.28$).

However, statistical analysis of the novelty-P3 component amplitudes for method 3 (which removed head motion artifact) revealed a main effect of Period ($F(1, 17) = 6.87$, $p = 0.020$, $\eta_P^2 = 0.29$) such that an increase in amplitude of the novelty-P3 component from early to late practice was observed (see figure 15).

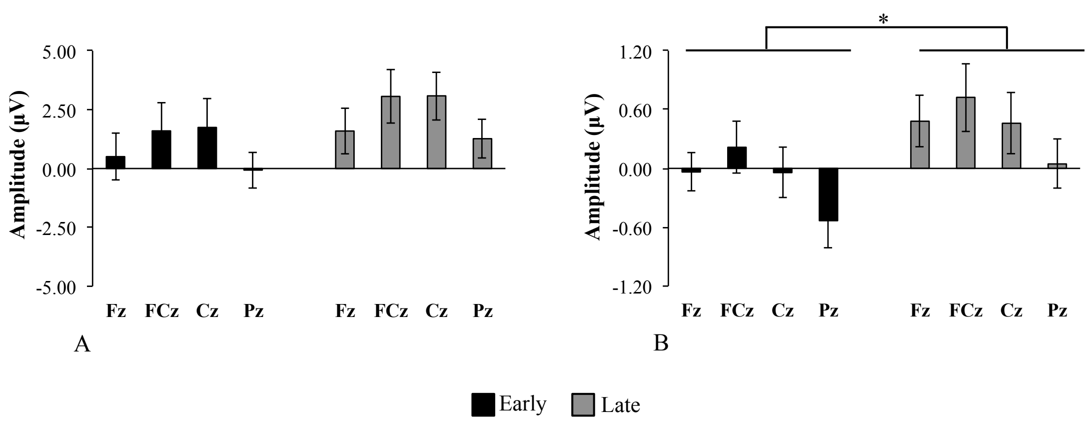


Figure 15: Novelty-P3 component amplitudes for the method which primarily removed eye blinks (panel A) and the method which also removed head motion artifact (panel B). Each plot shows amplitudes for early (black bars) and late (gray bars) practice for each sensor of interest (Fz, FCz, Cz, Pz). ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

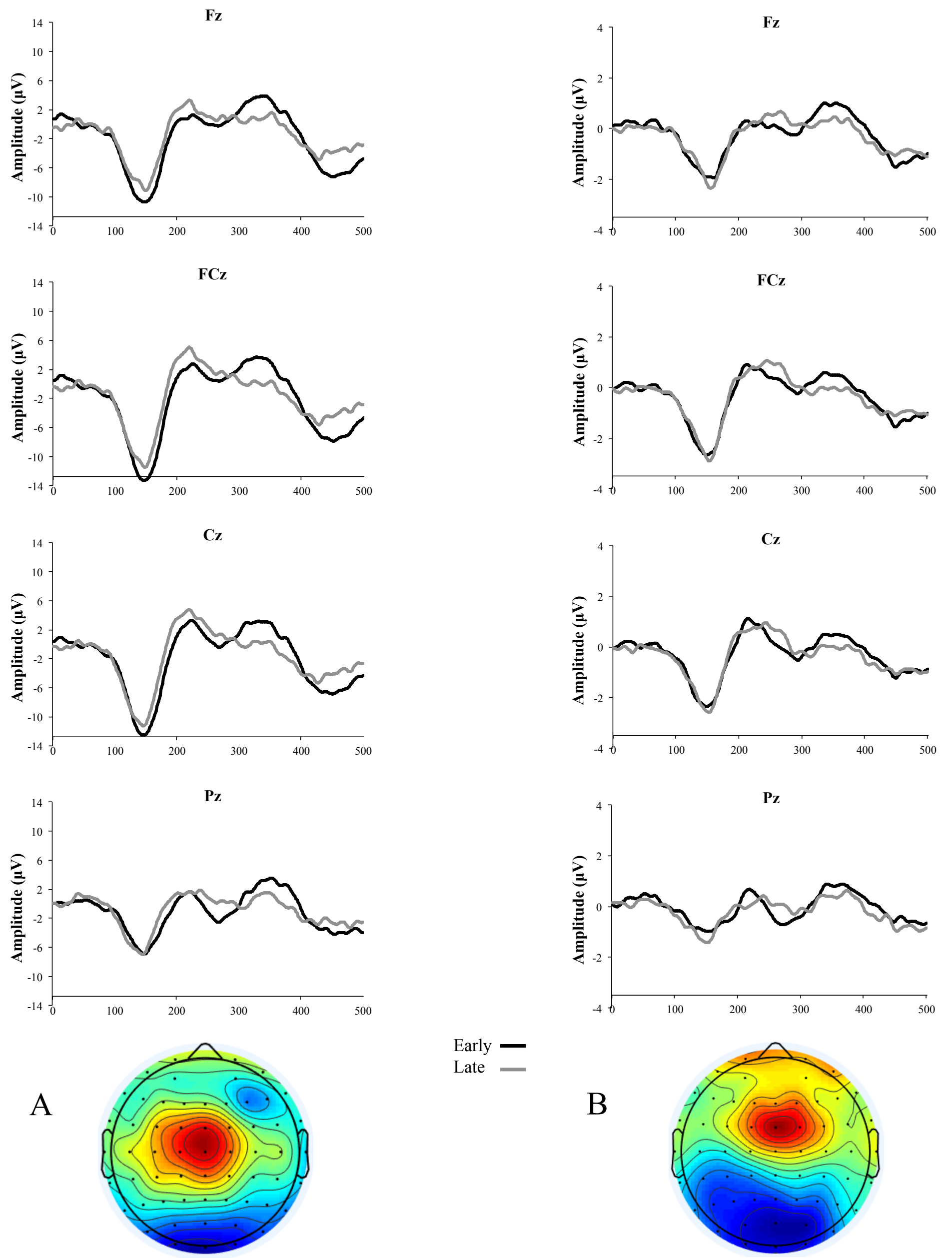


Figure 16: The first four row shows the grand-average ERP waveform for the method which primarily removed eye blinks (panel A) and the method which also removed head motion artifact (panel B). Each plot shows the grand-average for early (black lines) and late (gray lines) practice at each sensor of interest (Fz, FCz, Cz and Pz). The bottom row shows the topographic distribution of the novelty-P3 for each method.

Chapter 5: Study II Results – cognitive-psycho-motor processes during team performance

The following sections present the results of the second study. Specifically, the kinematic and NASA TLX post-test results are presented first (section 5.1), followed by the kinematic data from each of the teammate conditions (section 5.2). Lastly, the survey data from the teammate conditions is presented (section 5.3).

5.1 Comparison of post-tests

5.1.1 Performance metrics

Performance on the post-test on day one of testing compared to the post-test completed on day two showed a decrease in throughput ($t(18) = 2.13$, $p = 0.047$, $d = 0.24$). The other kinematic metrics did not reveal significant differences ($p > 0.05$)[5].

[5] All data presented for the post-tests has two subjects removed due to technical issues.

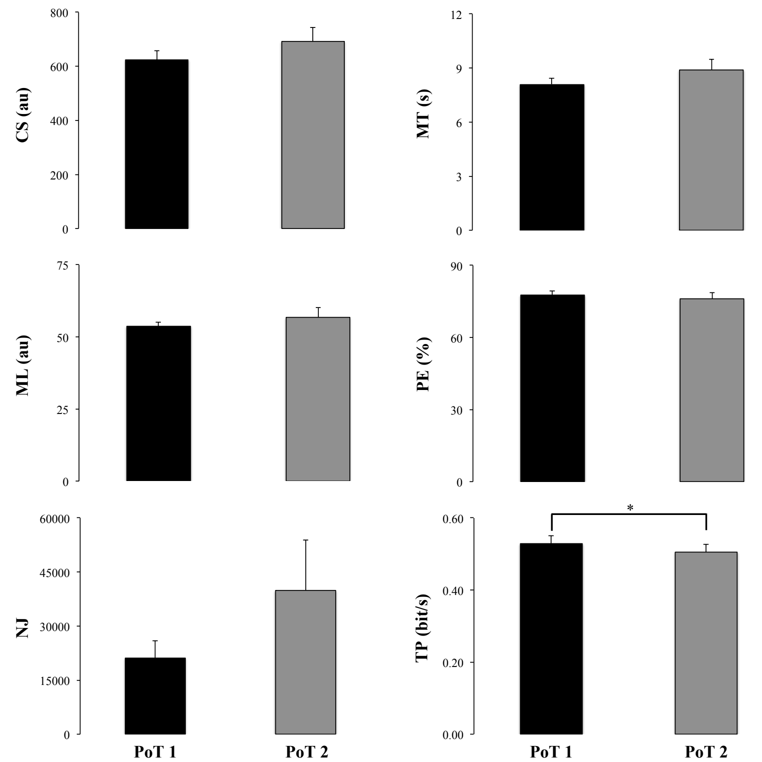


Figure 17: Kinematic performance during post-test 1 and post-test 2. CS: number of control signals, MT: movement time, ML: movement length, PE: path efficiency, NJ: normalized jerk, TP: throughput. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

5.1.2 NASA TLX

Analysis of the NASA TLX scores for the post-tests showed that there was a decrease in mental demand from the first post-test to the second post-test ($t(18) = 2.24$, $p = 0.038$, $d = 0.29$) as well as decrease in frustration ($t(18) = 2.98$, $p = 0.008$, $d = 0.61$). All other dimensions did not reveal significant differences ($p > 0.05$).

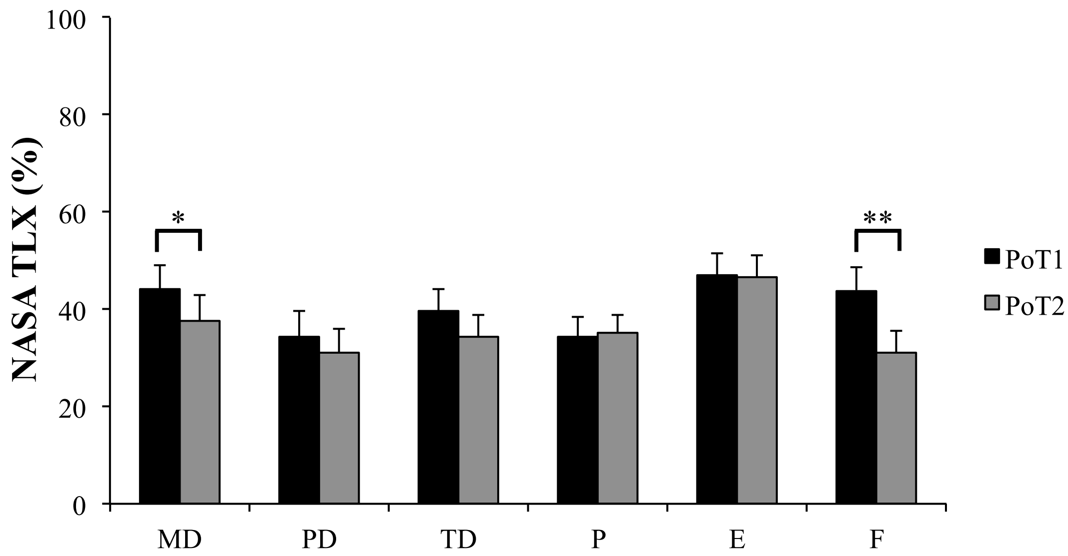


Figure 18: NASA TLX scores for post-test 1 (black bars) and post-test 2 (gray bars). MD: mental demand, PD: physical demand, TD: temporal demand, P: performance, E: effort, F: frustration. ***p < 0.001, **p < 0.01, *p < 0.05

5.2 Assessment of team kinematics

The findings revealed differences across conditions for all kinematic metrics (CS: $F(1.44, 25.85) = 46.62$, $p < 0.001$, $\eta_P^2 = 0.72$; MT: $F(2, 36) = 49.01$, $p < 0.001$, $\eta_P^2 = 0.73$; ML: $F(1.14, 20.56) = 28.88$, $p < 0.001$, $\eta_P^2 = 0.62$; PE: $F(1.18, 21.19) = 34.62$, $p < 0.001$, $\eta_P^2 = 0.66$; NJ: $F(1.45, 26.10) = 30.52$, $p < 0.001$, $\eta_P^2 = 0.63$; TP: $F(2, 36) = 57.81$, $p < 0.001$, $\eta_P^2 = 0.76$)[6]. Post-hoc analysis showed a decrease in control signals between the H-r and h-r conditions ($p < 0.001$, $d = 1.46$) as well as between H-r and h-R ($p < 0.001$, $d = 1.70$). There was also a decrease in movement time between H-r and h-r ($p < 0.001$, $d = 1.39$) as well as between the H-r and h-R conditions ($p < 0.001$, $d = 1.53$). Movement length as well as path efficiency showed differences between each condition. Specifically, there was a decrease in movement

[6] Kinematic data for the teammate conditions is missing two subjects due to technical issues. One subject's data is missing for the NASA TLX, trust and sense of attribution surveys.

length between H-r and h-r ($p = 0.001$, $d = 0.98$) as well as H-r and h-R ($p < 0.001$, $d = 1.70$).

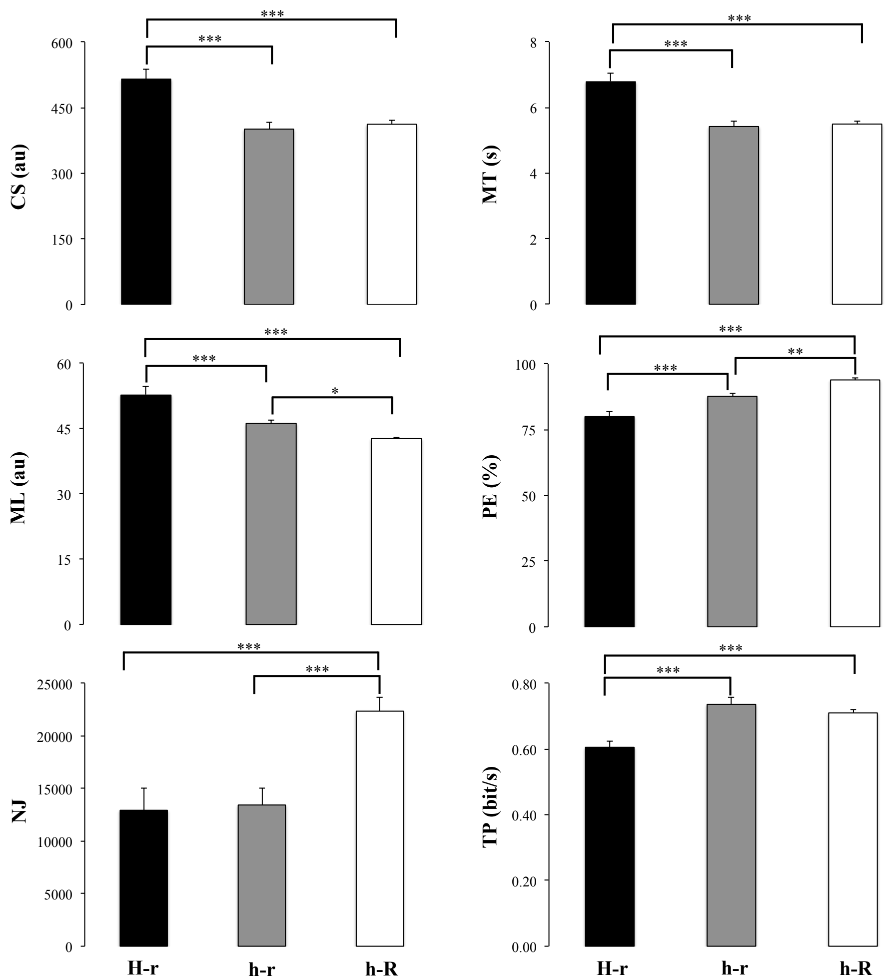


Figure 19: Kinematic performance during teammate conditions (H-r: human had most of the control, h-r: shared control, h-R: synthetic teammate has most of the control). CS: number of control signals, MT: movement time, ML: movement length, PE: path efficiency, NJ: normalized jerk, TP: throughput. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Additionally, there was a decrease in movement length between h-r and h-R ($p = 0.019$, $d = 1.38$). There was an increase in path efficiency between H-r and h-r ($p = 0.001$, $d = 0.96$) as well as H-r and h-R ($p < 0.001$, $d = 1.79$). There was also increase in path efficiency between h-r and h-R ($p = 0.004$, $d = 1.37$). There was an increase in normalized jerk for h-R in comparison to H-r ($p < 0.001$, $d = 1.41$) and h-r ($p < 0.001$, $d = 1.39$); however, this difference is due to a limitation in the programming of the synthetic teammate. Lastly, there was an increase in throughput when comparing H-r to h-r ($p < 0.001$, $d = 1.38$) as well as in comparison to h-R ($p < 0.001$, $d = 1.45$).

5.3 Assessment of team surveys

5.3.1 NASA TLX

Statistical analysis of the NASA TLX scores across the different manipulations of interdependence (H-r, h-r and h-R) revealed a main effect of Condition for mental demand ($F(1.21, 22.92) = 4.33$, $p = 0.042$, $\eta_P^2 = 0.19$).

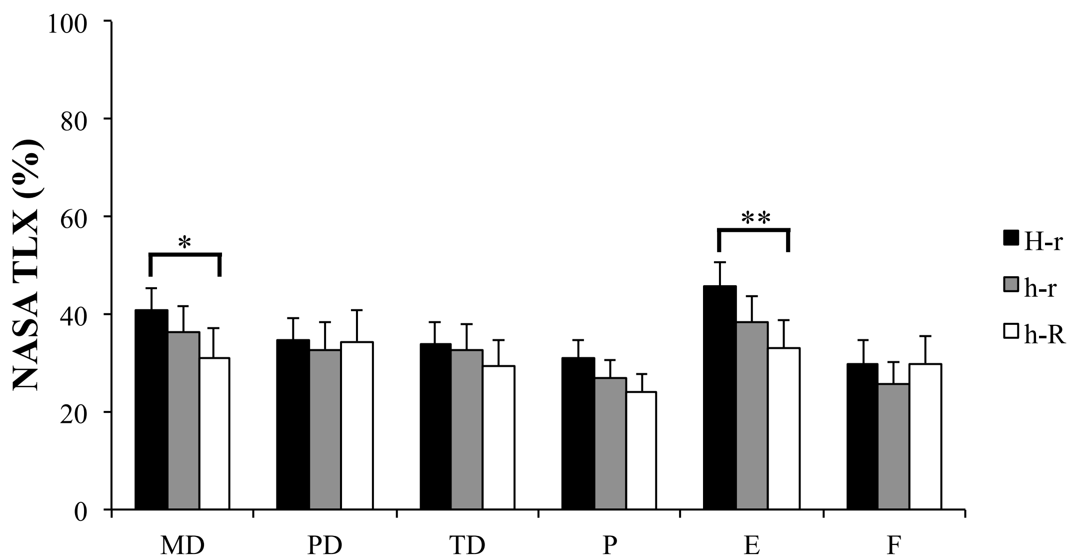


Figure 20: NASA TLX scores for teammate conditions (H-r: human had most of the control (black bars), h-r: shared control (gray bars), h-R: synthetic teammate has most of the control (white bars)). MD: mental demand, PD: physical demand, TD: temporal demand, P: performance, E: effort, F: frustration. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Post-hoc analysis revealed a decrease in mental demand from the H-r to the h-R condition ($p = 0.020$, $d = 0.67$). There was also a main effect of Condition for the effort dimension ($F(2, 38) = 5.09$, $p = 0.012$, $\eta_P^2 = 0.21$). Post-hoc analysis showed a decrease in effort from the H-r in comparison to the h-R condition (p = 0.008, d = 0.66). There were no differences for the other dimensions of the NASA TLX.

5.3.2 Efficacy beliefs

Statistical analysis revealed no significant differences for self-efficacy or collective efficacy.

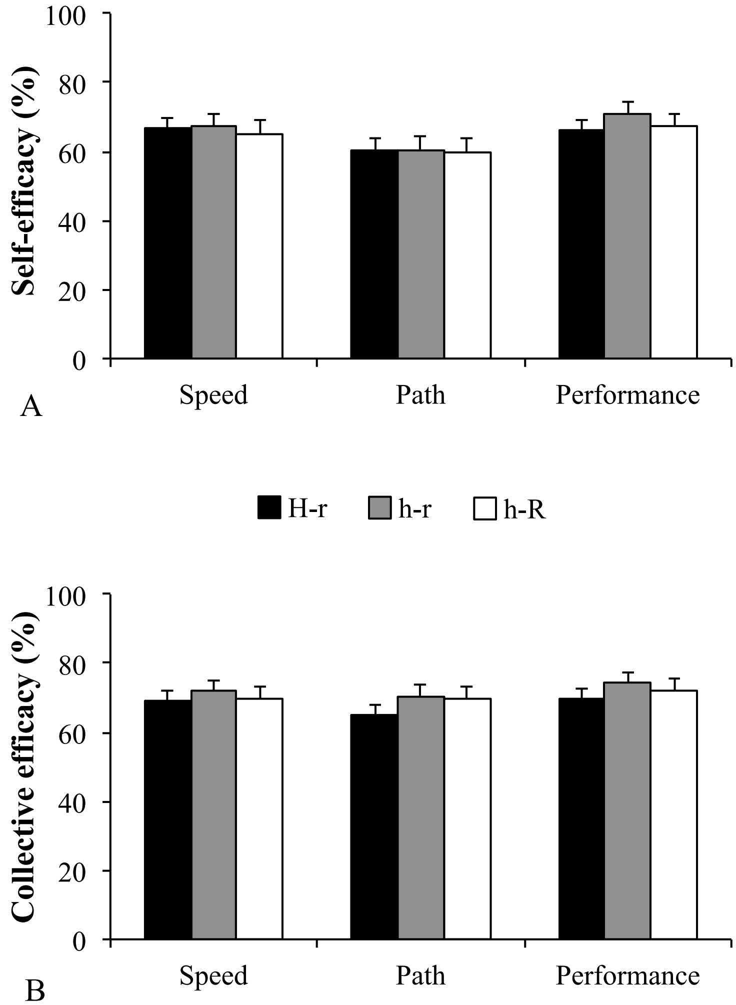


Figure 21: Self-efficacy (panel A) and collective efficacy (panel B) scores for teammate conditions (H-r: human had most of the control (black bars), h-r: shared control (gray bars), h-R: synthetic teammate has most of the control (white bars)). Speed: reaching the targets as fast as possible, Path: reaching the targets as straight as possible, Performance: overall performance of the task ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

5.3.3 Trust

Our findings showed no significant differences in regards to how much the participant trusted the synthetic teammate to move as fast as possible. There was a main effect of Condition regarding their trust in the synthetic teammate moving as straight as possible ($F(1.11, 21.09) = 5.80$, $p = 0.022$, $\eta_P^2 = 0.23$).

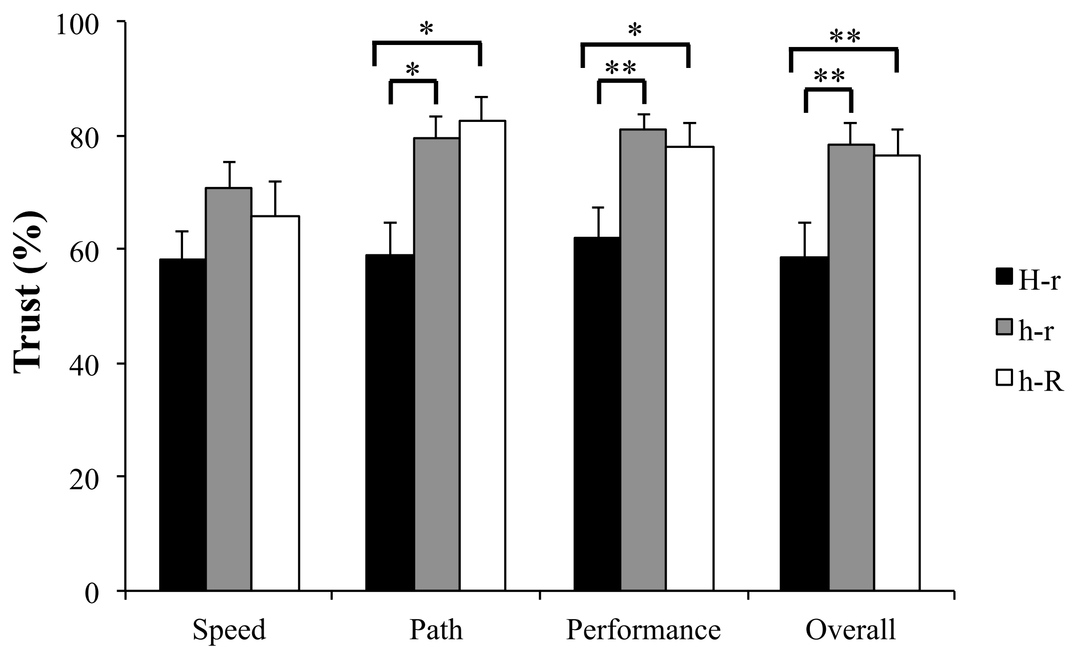


Figure 22: Trust scores for teammate conditions (H-r: human had most of the control (black bars), h-r: shared control (gray bars), h-R: synthetic teammate has most of the control (white bars)). Speed: To what extent do you trust your teammate to reach the targets as fast as possible?, Path: To what extent do you trust your teammate to reach the targets as straight as possible?, Performance: To what extent do you trust your teammate to perform this reaching task well?, Overall: Overall, how much do you trust your teammate? ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

The post-hoc analysis revealed an increase in trust for h-r ($p = 0.020$, $d = 0.67$) as well as h-R ($p = 0.011$, $d = 0.72$) in comparison the H-r condition. Additionally, main effects of Condition were found for trust in the teammate's ability to perform the task well ($F(1.36, 25.90) = 7.04$, $p = 0.008$, $\eta_P^2 = 0.27$) and overall trust in the teammate ($F(1.42, 27.01) = 8.05$, $p = 0.004$, $\eta_P^2 = 0.30$). Post-hoc analyses revealed that for trust in the teammate's ability to perform the task, there was an increase in trust from the H-r condition to h-r ($p = 0.004$, $d = 0.89$) as well as the h-R condition ($p = 0.012$, $d = 0.73$). Similarly, for overall trust in the teammate there was an increase in h-r ($p = 0.002$, $d = 0.85$) as well as h-R ($p = 0.007$, $d = 0.71$) in comparison to the H-r condition.

5.3.4 Sense of attribution

Statistical analysis of the sense of attribution scores revealed that in the context of their team relative to an extraneous stimulus for both the locus of causality and the personal dimension, there were no significant differences across conditions.

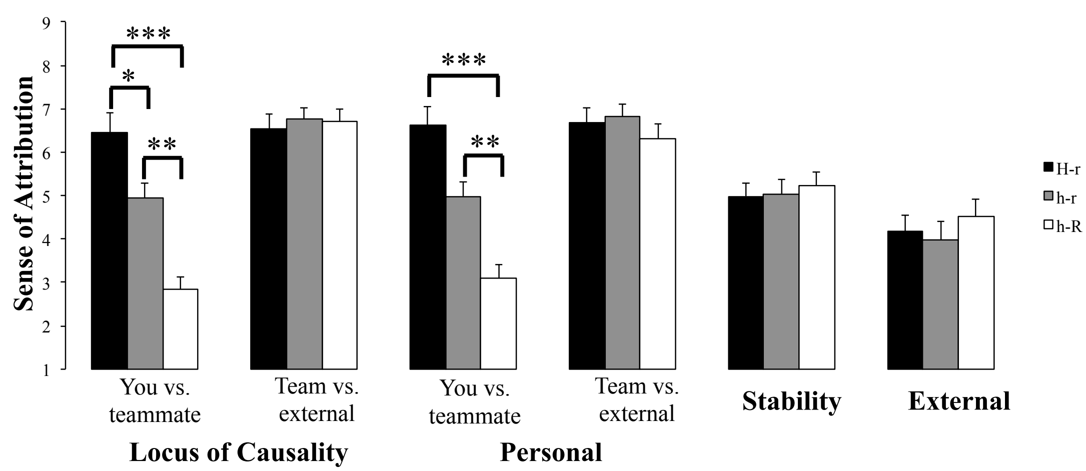


Figure 23: Sense of attribution scores (H-r: human had most of the control (black bars), h-r: shared control (gray bars), h-R: synthetic teammate has most of the control (white bars)). The locus of causality and personal dimensions both included questions concerned with the participant's perception of internal (to themselves or to the team) vs. external (to the teammate or to an extraneous stimulus) control. Smaller values are representative of a stronger belief in external factors contributing to the outcome. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Similarly, for the dimensions of stability and external control showed no significant differences between the different teammate conditions. Analysis of the locus of causality dimension, when participants considered themselves in comparison to their teammate revealed a main effect of Condition ($F(2, 38) = 23.62$, $p < 0.001$, $\eta_p^2 = 0.55$). Post-hoc analysis showed decreases in their sense of control from the H-r condition in comparison to the h-r condition (p = 0.02, d = 0.82) and the h-R condition ($p < 0.001$, d = 2.13). Additionally, a decrease in their sense of control was found when comparing h-r to the h-R condition (p = 0.001, d = 1.43). Also, analysis of the personal dimension, when participants considered themselves in comparison to their teammate showed a main effect of Condition ($F(1.41, 26.87) = 19.70$, $p < 0.001$, $\eta_P^2 = 0.51$). Post-hoc analysis revealed decreases when comparing the H-r ($p < 0.001$, d = 1.76) and the h-r (p = 0.001, d = 1.19) conditions to the h-R condition.

Chapter 6: Discussion

6.1 De-noising method comparison

6.1.1 Spectral

By employing a similar approach to previous methods (Daly et al., 2013; Onikura et al, 2015), we were able to demonstrate that the proposed de-noising method (method 3) appears to identify and remove artifacts in the cortical regions and frequency bands of interest. It is important to note that method 3 addresses several concerns about artifact contamination in EEG signals. First, similar to method 2, method 3 results in a large reduction of theta power in the frontal regions, which is likely due to the removal of ocular artifacts. Furthermore, method 3 continues to show a greater reduction of power across the other cortical regions in the theta frequency band, which is consistent with removal of head motion artifact occurring at lower frequency bands (Daly et al., 2013; Onikura et al., 2015).

Visual observation of the power reduction obtained with method 2 suggests that a larger reduction in the low-/high- alpha power bandwidth tended to occur in the frontal region compared to other regions and frequency bands. This also highlights the emphasis this method places on removal of ocular artifacts, which range from 1-13Hz (Abo-Zahhad et al., 2015). However, for these two frequency bandwidths the use of method 3 led to a larger reduction of spectral power across all cortical regions. Such an elevated reduction of power for low and high-alpha in method 3 may have resulted from an overly conservative approach, where too many independent components were removed.

Finally, compared to method 2, method 3 resulted in a larger reduction of spectral power across all cortical regions (in particular in the temporal and occipital regions) in the low-beta and high-beta frequency bandwidths, although this difference was more prominent in the high-beta. Additionally, it is important to note that for method 3 the increased reductions of power in the temporal and occipital regions for low as well as high-beta are most likely due to removal of muscle artifact (Daly et al., 2013; Muthukumaraswamy, 2013). Hence, method 3 not only removes ocular artifacts, which are localized to the frontal region, it also removes muscle related activity in the temporal, parietal and occipital regions from the EEG signal.

6.1.2 ERP

The ERP analyses of the novelty-P3 component with methods 2 and 3 yielded fairly different results. For method 2, which primarily focused on removal of ocular artifacts, only 10 out of 19 participants could be included in the analysis due to an excessive amount of noise in the EEG data. As previously mentioned, based on analysis of these subjects a time window of 220-260ms was identified, which is earlier than most windows identified in the literature (Miller et al., 2011; Rietschel et al., 2014; Shaw et al., 2018). Additionally, the topographic map at sensor FCz where the novelty-P3 was found to be maximal shows the distribution to be more centrally located (see figure 16), which is not necessarily in accordance with other literature which suggests that the novelty-P3 is frontally located (Barry et al., 2016; Polich, 2007; Shaw et al., 2018). Comparatively, method 3 (where head motion artifacts were removed), allowed for inclusion of all participants except for one and a window of 246-286ms was identified. This window is consistent with prior work, which reported increases in the amplitude of the novelty-P3 throughout practice of a trial based task (Rietschel et al., 2014). Furthermore, the topographic map at sensor FCz for this analysis shows a more frontally located distribution, which is consistent with previous research (see figure 16; Barry et al., 2016; Polich, 2007; Shaw et al., 2018).

6.2 Combined changes in attentional reserve and cognitive-motor effort during practice of reaching movements

6.2.1 Performance throughout practice

Overall, participants improved their performance throughout the practice session. Specifically, our results revealed that from early (first 50 trials) to late (last 50 trials) practice, participants were able to move the arm faster (reduced movement time), straighter (attenuated movement length and increased path efficiency), and smoother (reduced normalized jerk). In addition, participants revealed a reduction in the number of control signals as well as an increase in throughput, which suggest a refined communication when controlling the robotic arm and a higher amount of information sent to the end-effector. Overall, these findings suggest that as the participants practiced the task, performance improved which is consistent with previous similar research (Shuggi et al., 2017, 2018, 2019).

6.2.2 Assessment of cognitive-motor effort

Although examination of spectral power during early planning (-2 to -1 second before movement onset) did not reveal any changes in theta power, late planning (-1 to movement onset) revealed a significant increase from early to late practice for method 2, which is consistent with the findings of prior research (Gevins et al., 1997; Gentili et al., 2011; Perfetti et al., 2011; Jaquess et al., 2018). It must be noted, that although head motion was not removed for method 2, this finding is most likely not a false positive since no movement occurs during the late planning stage. This increase in theta could indicate increased recruitment of focused attentional resources as participants plan their movement (Gevins et al., 1997; Ishii et al., 2014). More specifically, it is possible that the increased activation of theta is related to the recruitment of the learned internal model, which encoded the sensorimotor mapping between head movements and the robotic end-effector displacements (Bursztyn et al., 2006). Lastly, this increased focus of attention during the planning stage could contribute to the improved performance observed during the execution stage (Jaquess et al., 2018; Weber & Doppelmayer, 2016).

As predicted, during early and late planning, an alpha synchrony was detected for both methods. More specifically, for both methods an increase in low-alpha power was observed during both planning stages. Such changes in alpha power have been shown to reflect decreased recruitment of cortical resources throughout practice (Gevins et al., 1997; Gevins & Smith, 2000; Gentili et al., 2011; Jaquess et al., 2018). In particular, increases in low alpha have been related to decreased general cortical arousal, while increased high alpha power has been associated with decreased recruitment of task-related cognitive processes (Gevins et al., 1997; Hatfield et al., 2013; Miller et al., 2014; Jaquess et al., 2018). Furthermore, a decrease in recruitment of both general and task-specific cortical resources implies that participants required less cognitive-effort to plan their movements as progressing through practice. This finding is consistent with prior research, which showed that as a novel visuomotor mapping is learned the need for inhibitory functions modulated by alpha decreases throughout adaptation (Gentili et al., 2011). Such a finding is also consistent with research showing that increases in alpha occur simultaneously with improved performance (Kerick et al., 2004). While low-alpha synchrony was observed for both methods, increase of high-alpha power was only observed in method 2. Such a high-alpha synchrony during practice is also consistent with prior studies discussed above. Although head motion was not removed with method 2, these results and their interpretation appear to be reasonable since no movement occurred during the planning stage. Also, the absence of an observed increase in high-alpha may be due to an overly conservative approach when applying method 3. Specifically, method 3 may possibly mask a noticeable increase in high-alpha power detected by method 2 during the planning stage (although no significant difference was observed during planning with method 3, it should be noted that $\eta_P^2 = 0.12$ for both planning stages, which is not neglectable).

Interestingly, while during the execution stage method 2 revealed a stable level of high-alpha power, the low-alpha synchrony suggests a decrease of general arousal. Although, we cannot completely rule out that the detected low-alpha synchrony with method 2 during execution is due to head motion artifact, there are several arguments which suggest that it is unlikely the case. First, head motion artifact primarily affects lower frequency bands such as the theta band (Onikura et al., 2015). Second, if head motion was driving the EEG power in this band, it would likely have caused a reduction since as participants learn the new mapping, control of the arm is enhanced and less head motion is needed. Third, this study did not focus on a specific biomechanical event such as head movement initiation, but instead on mental workload, which is not necessarily synchronized with such events (Kline et al., 2015; Shaw et al., 2018). Fourth, it must be noted that similar findings were observed with method 3, which removed head motion artifacts. Specifically, while high-alpha power remained unchanged, a tendency (p = 0.087; η_P^2 = 0.16) of increase in low-alpha power was observed.

In addition, the lack of high-alpha synchrony revealed in both methods during execution, may be representative of a need to continue recruitment of task-related cognitive processes to complete the reaching movement, while maintaining improved performance (Miller et al., 2014). This is consistent with our previous work, which although behavioral, revealed that performance and mental workload (indexed with NASA TLX) dynamics improved at different rates throughout multiple practice sessions (Shuggi et al., 2019). Since NASA TLX has been shown to be reflective of EEG metrics of mental workload, it is reasonable to predict a similar evolution of high-alpha throughout multiple practice sessions (e.g., Shaw et al., 2018; Ke et al., 2014). Thus, future examination of cortical activity over multiple practice sessions may reveal a delayed increase in high-alpha power compared to performance and possibly to low-alpha power. Additionally, the overall changes observed during execution and planning stages are consistent with prior work, which showed that changes in the alpha bandwidth are less pronounced during execution relative to the planning stages. This could be due to the need to actively engage movement related processes such as visual feedback (Gentili et al., 2011).

Although throughout the literature multiple interpretations regarding changes in beta power can be contemplated; the increase of power in this frequency bandwidth observed here is consistent with prior work, which suggests that beta synchrony is representative of learning (Boonstra et al., 2007; Moisello et al., 2015; Pollock et al., 2014). This is also in agreement with previous investigations, which have suggested that performance improvement accompanied with beta synchrony could be indicative of cortical reorganization in certain regions due to learning a novel skill (Boonstra et al., 2007; Pollock et al., 2014). In particular, throughout practice both method 2 and 3 revealed low-beta synchrony for both early and late planning. It is important to note that only method 2 identified a specific elevation of low-beta power frontally for both early and late planning. This is consistent with the notion that an elevation of frontal beta power could be due to a refinement of attentional mechanisms throughout practice (Moisello et al., 2015).

For method 2 a reduction of high-beta power in the temporal regions during early planning is observed whereas in late planning an increase and decrease of high-beta power was detected in the frontal and temporal regions, respectively. Similarly, during the execution stage only method 2 detected an increase of low and high-beta power in the frontal region along with low-beta desynchrony in the temporal region.

Overall, it is possible that decreases in beta power within the temporal region across the stages of planning and execution could be due to the reduction of muscular activity as participants learn to better prepare for execution of the reaching movement (Lay et al., 2002). Additionally, it is important to note that although method 2 did not identify head motion artifact, the increases in beta during planning are most likely not due to muscle artifact since there was no movement. While there may have been slight muscle tension in the neck as participants prepared to move, it is unlikely that this muscle tension would appear in the frontal region (Muthukumaraswamy, 2013). Furthermore, the increases in beta during execution for method 2 are partially supported by method 3, which showed tendencies towards significance in low and high-beta (Period x Region interactions - low beta: $p = 0.0812$, $\eta_P^2 = 0.14$; high beta: $p = 0.060$, $\eta_P^2 = 0.14$). Additionally, even though frontal muscle activity could be in the range of 20-30Hz, as previously mentioned muscle activity has been shown to decrease throughout practice (Lay et al., 2002; Muthukumaraswamy, 2013).

6.2.3 Assessment of attentional reserve throughout practice

In the context of attentional reserve assessment throughout practice, the increase in amplitude of the novelty-P3 component from early to late practice is consistent with prior research (Rietschel et al., 2014). It must be noted that a significant increase was only observed for method 3, which removed head motion artifact and not for method 2[7], which primarily focused on the removal of ocular artifacts. The lack of significance for method 2 was most likely due to a large loss of data corrupted by the head motion artifacts. Specifically, this increase in amplitude reflects a decrease in the allocation of attentional resources to the reaching task as participants completed the practice session. This decrease in the recruitment of attentional resources for the reaching task allowed for an allotment of resources to the auditory stimuli. Furthermore, it is important to note that as participants reduced their allocation of attentional resources towards the task, their performance continued to

[7] It must be noted that a tendency of increase of the novelty-P3 amplitude for method 2 ($F(1, 9) = 3.56$, $p = 0.091$, $\eta_P^2 = 0.28$) was observed, which further confirms our findings.

improve. As previously mentioned, participants were able to move the arm faster, straighter and more smoothly to reach the targets throughout the workspace. These results align with those reported by Rietschel and colleagues (2014), who also employed a discrete task to examine attentional reserve throughout practice. As previously mentioned, the window identified in this work for the novelty-P3 (246-286ms) is consistent with that reported by Rietschel and colleagues (2014; 250-290ms). These windows are slightly earlier than those identified for continuous tasks when assessing attentional reserve during motor performance (Miller et al., 2011; Shaw et al., 2018). Thus, it may be possible that a shift occurs in the allocation of resources during information processing of a discrete task compared to a continuous task.

Rietschel and colleagues (2014) also suggest an alternative possibility to the interpretation of the task requiring less attentional resources throughout practice. They suggest that it is possible for participants to have developed "task-specific attentional flexibility," which would allow them to orient towards the novel sound and then quickly return their attention to the task. While they acknowledge this potential alternative, it is also noted that regardless of interpretation, the outcome of increase in available attentional resources is the same. A possible way to examine this difference in interpretation would be to examine the re-orientation negativity (RON) component, which in this context represents disengagement from the novel auditory stimuli and re-orientation towards the reaching task (Scheer et al., 2016).

6.2.4 Conclusions, limitations and future work

Overall, throughout practice performance improved, while reductions in cognitive-motor effort were observed along with increases in attentional reserve, representing an attenuation of mental workload. Hence, attentional reserve and cognitive-motor effort can be used to collectively assess mental workload throughout practice (Jaquess et al., 2017; Shaw et al., 2018). Specifically, increases in theta and beta throughout the planning stages (in the absence of head movement), could reflect increases in focused attention and refinement of attentional mechanisms, respectively. Furthermore, increases in alpha power suggest a reduction of the recruitment of cortical resources throughout practice; in particular, during planning where increases in both low and high-alpha are more pronounced. These results are supported by cognitive load theory, which suggests that overtime schemas are constructed and the information is grouped into larger parts; such schemas can then be used unconsciously (Paas et al., 2003, 2010). When schemes are processed unconsciously, automatic processing is being used, which activates a learned sequence from long-term memory and does not place any burden on the individual's capacity limit (Paas & Van Merrienboer, 1994; Schneider & Shiffrin, 1977). Hence, participants may have, to some extent, constructed schemas by encoding an internal model of the novel sensorimotor mapping between head movements and end-effector displacements. Such an encoding would have allowed them to decrease recruitment of cortical resources when planning their movements. The lack of increase in high-alpha during the execution stage could be indicative of the need for additional practice (Shuggi et al., 2019).

As previously mentioned, the proposed de-noising method (method 3) was effective in reducing noise in lower frequency bands where eye blinks and head motion during movement execution occur as well as noise in higher frequency bands where muscle activity occurs. It is possible that an excessive removal of independent components may have contributed to limiting the identification of spectral changes such as those in the alpha frequency band. Future work will refine this approach by assessing the use of a threshold mechanism when removing independent components correlated with head motion. Specifically, cross correlation values of the EEG and IMU data could be normalized by the autocorrelation and then a predetermined threshold could be applied. A threshold could be chosen empirically or based on prior literature, which used a threshold of two standard deviations above the mean correlation (Daly et al., 2013). However, it is important to note that while the de-noising method may have excessively removed components for the spectral analysis, it appears to have been effective in the analysis of the novelty-P3 component. As previously mentioned, removal of the head motion artifacts provided a more accurate topographic distribution and time window (Rietschel et al., 2014).

In regards to the assessment of mental workload throughout practice via a combined approach, this study was limited by only including one practice session. As previously mentioned, our prior work suggests that multiple practice sessions can reveal greater insight into performance and mental workload dynamics (Shuggi et al., 2019). Hence, future work will use EEG to employ such a combined approach during multiple practice sessions, which could provide a more comprehensive examination of changes in mental workload throughout practice. In particular, employment of

EEG would allow for examination of cortical dynamics to better understand the rate of cortical refinement as well as allocation of attentional resources throughout motor practice.

6.3 Cognitive-psycho-motor processes underlying team dynamics

6.3.1 Changes in performance and mental demand between post-tests

While our prior work suggests that multiple practice sessions are necessary before performance completely stabilizes; the comparison of the post-tests revealed sufficiently stable performance (Shuggi et al., 2019). Additionally, participants reported lower mental demand and frustration after completing the second post-test in comparison to the first post-test. These decreases in mental demand and frustration could be due to the order in which the post-tests were completed each day. Specifically, post-test 1 was completed after participants had already completed the practice session consisting of 200 targets; however, post-test 2 was the first reaching task completed on the second day of testing. Hence, participants' perceived mental demand and frustration could have been higher after the first post-test due to residual effects from the practice session.

6.3.2 Examination of teammate conditions

As predicted, the condition where the synthetic teammate had most of the control overall revealed the best performance (i.e., faster and straighter movements were used to reach the target). Additionally, as we predicted overall performance in the h-r condition was better than the H-r condition, which indicated that even when control is shared, the synthetic teammate is able to assist in the completion of faster and straighter movements throughout the workspace. It must be noted that although, normalized jerk was significantly higher for the h-R condition in comparison to the h-r and H-r conditions, this was due to the programming of the teammate. Thus, although reported, the normalized jerk cannot be considered as a result of the experimental manipulation.

Based on cognitive load theory, we had initially expected that the additional requirement of coordinating with a teammate when control of the virtual robotic arm was shared would increase mental workload (Kirschner et al., 2009). Specifically in the context of individuals working together, cognitive load theory suggests that as task complexity increases and individuals are placed into high load conditions, the cost of coordination is expected to be less than the gain of dividing the labor among a larger cognitive capacity. While under a low mental workload conditions, it is expected that the cost of coordination will outweigh any gain from the division of labor because an individual can most likely complete the task alone (Kirschner et al., 2009). Hence, it was predicted that since participants had practiced the reaching task alone first and reached a certain level of proficiency, the addition of a teammate with equal levels of dependence would increase their mental workload.

Contrary to expectations, perceived mental demand for the H-r condition did not differ from the h-r condition; however, as predicted the former resulted in a higher perceived mental demand relative to the h-R condition. In addition, the h-r and h-R conditions did not significantly differ in perceived mental demand. Similar results were obtained when considering the effort dimension of the NASA TLX survey. Taken together these results suggest that increased control by the synthetic teammate, may have allowed participants to outsource some of the mental demand and effort required to complete the reaching task, in particular in the h-R condition. Additionally, shared control in this situation may have required less coordination between the teammates than initially expected, aligning with previous work showing that intermediate levels of automation can be effective (Kaber & Endsley, 2004). Although not significantly different at every level of increase in teammate control, it is interesting to observe the gradual decrease in mental demand and effort. The directionality of these results is in alignment with prior work showing that working with a robotic teammate can decrease mental workload (Harriott et al., 2015).

In addition, contrary to expectations varying team interdependence in this task did not affect efficacy beliefs. This is consistent with a recent study where individuals learned (alone) to operate the HMI employed here and which suggests that compared to performance and mental workload, the development of self-efficacy beliefs can be delayed in part due to a lack of reference for quality performance (Shuggi et al., 2019). The author suggests an additional possible explanation is that mental workload may influence efficacy beliefs. Namely, Kanfer and Kanfer (1991) proposed that efficacy beliefs are part of the self-regulation process, which is defined as intrapersonal processes an individual controls to direct persistence, affect, and behavior for goal attainment. They further suggested that based on Kanfer and Ackerman's (1989) Integrative Resource Allocation Model of Learning and Task Performance, self-regulatory processes during task performance require some attentional resources. Thus, self-regulation may be limited if there are not enough attentional resources available (i.e., the task requires all attentional resources).

Furthermore, it has been shown that there may be an optimal level of self-efficacy in relation to mental effort and performance (Clark, 1999; Kanfer & Kanfer, 1991; Ede et al., 2017). Thus, in the context of this framework, it is possible that due to a lack of attentional resources for self-regulation participants were not able to accurately assess their efficacy beliefs.

Furthermore, when individuals perform a task in which they are considered to be novices, in most instances they have prior experience and/or knowledge from which to establish a standard of quality performance, which by design is not the case for our experimental platform (Trope, 1983; Bandura, 1997). In addition, since collective efficacy is a construct based on the views of each team member it is possible that the lack of reference would also impact the participants' ability to accurately assess their belief in their team's performance (Bandura, 1997; Myers et al., 2004; Stajkovic et al., 2009).

Our findings related to the trust of the teammate in each condition did not support our hypotheses. Interestingly, there were no significant differences between teammate conditions in the context of trusting the synthetic teammate to move as fast as possible; however, there were differences for all other aspects of trust. Importantly, increases in trust of the synthetic teammate as the teammate acquired more control from the H-r condition, mostly align with the decreases observed in perceived mental demand. Specifically, participants' trust in their teammate increased in the context of their teammate's ability to take the straightest path and perform the task well. Such increases in trust result in a willingness to outsource some of the control to the teammate, which could result in a reduction of mental workload. However, such increases in trust and decreases in mental workload could also lead to complacency, which is defined as an overreliance on automation (Parasuraman et al., 2000; 2008). Also, overall trust in their teammate increased as their teammate's control became elevated from the H-r condition, which could mean that the participant's perception of their teammate's contribution largely impacted how much they trusted their teammate. Such a result is supported by other work indicating that increased trust in the synthetic teammate can lead to a decrease in perceived effort, which is observed in the NASA TLX results (Broad et al., 2017). Lastly, it is important to note that no significant differences in trust were found between the conditions of shared control (h-r) and the synthetic teammate having most of the control (h-R) for any dimension of the trust survey. Hence, while increasing the teammate's control from the h-r to the h-R condition did result in a significantly straighter path to reach the target, participants' trust in their teammate's abilities to follow the straightest path and perform the task well was unaffected.

Sense of attribution findings showed significant differences between teammate conditions for the locus of causality and personal dimensions. Specifically, the locus of causality dimension (i.e., internal vs. external control; Weiner, 1985) when considering the participant vs. the synthetic teammate revealed significant decreases as the teammate's control increased. Such reductions indicate that as the synthetic teammate gained control, the participants perceived themselves to be less responsible for the team's outcomes. Similarly, for the personal dimension, which is representative of the controllability (i.e., do you have control vs. does someone else have control; McAuley et al., 1992; Weiner, 1985), when considering the participant vs. the teammate showed significant decreases as the teammate gained more control. However, significant findings were only revealed between the H-r relative to the h-R condition and between the h-r relative to the h-R condition. Interestingly, although, a decrease in perceived sense of attribution was observed from H-r to h-r, this was not statistically different, which suggests that the sense of attribution for this dimension tends to be more maintained in the shared control condition. Furthermore, these changes observed for the locus of causality and personal dimensions serve as manipulation checks that the participants did perceive the teammate as having more control in the h-r and h-R conditions. Interestingly, regardless of whether participants were in a reciprocal condition or the shared condition, their sense of stability did not significantly change.

In summary, it appears that when compared to the two levels of interdependence where the synthetic teammate had more control (h-r or h-R conditions), the condition where the human participant mostly controlled the robotic arm, overall resulted in i) a deterioration of motor performance, ii) increases in perceived mental workload, iii) a decrease of trust in the teammate and iv) a greater sense of control.

When considering the two levels of interdependence of shared control (h-r) and where the synthetic teammate mostly controls the robotic arm (h-R), it appears that the level of mental workload and trust are similar while the majority of the kinematic parameters (CS, MT, TP) are comparable (except ML and PE). Furthermore, shared control (h-r) tended to maintain a sense of attribution (for the personal dimension) similar to the level of interdependence where the human has most of the control of the robotic effector (H-r). This is important, since a reduction of sense of attribution could lead to negative emotions, which longer term may negatively impact efficacy beliefs (Allen et al., 2009; Chow & Feltz, 2008; Weiner et al., 1979). Furthermore, such a reduction in sense of attribution is important since it was demonstrated that a lack of control on the human's part in combination with increased trust might lead to complacency (Parasuraman et al., 2008). Therefore, when considering the cognitive-motor processes as well as psychological factors examined in this study it appears that overall the shared control condition may have been the most beneficial trade-off, which is consistent with prior research (Kaber & Endsley, 2004; Parasuraman et al., 2000). Thus, even though when the teammate had most of the control the best performance and lowest perceived mental demand was achieved, there are other factors of the human teammate as well as the human-robot relationship, which must be considered.

6.3.3 Future work and limitations

While implementation of the synthetic teammate provided precise control, future work could employ a neurocontroller with more advanced adaptive capabilities to further examine team dynamics. Additionally, varying the level of task difficulty with the teammate at different levels of interdependence could provide information regarding the optimization of performance as well as mental workload while limiting the risk of complacency.

Lastly, due to technical difficulties EEG data could not be included for this second study. While analysis of behavioral data did provide some insight into the cognitive-psycho-motor processes underlying team dynamics, incorporation of neuroimaging could provide additional information. Specifically, examination of cortical dynamics during performance with the synthetic teammate could reveal information regarding the human's mental workload throughout performance. Understanding possible changes in mental workload throughout performance of the task with the synthetic teammate at different levels of interdependence could inform how the synthetic teammate adapts to the human user.

6.4 HMI to inform cognitive-psycho-motor processes

Due to the highly interdisciplinary nature of both studies, this work could have a broad impact in both cognitive-motor neuroscience and robotics. The first study enhances existing literature regarding cognitive-motor practice by employing a combined approach to assess cognitive workload. Specifically, this dual approach allows for examination of attentional reserve as well as cognitive-motor effort during practice of a task via a human-machine interface. This work can inform our understanding of the cognitive-motor mechanisms at work during practice of a novel task and better improve training protocols for various types of cognitive-motor tasks.

In the second study, the use of a simple synthetic partner allows this work to be applicable to human team dynamics as well as human-robot team dynamics. Team dynamics are extremely relevant in the field of cognitive-motor neuroscience due to the interactive nature of many cognitive-motor tasks (i.e., sports teams or any dyads that involve human performance (e.g., aircraft pilots)). Hence, the results of this study could inform how teams practice a particular skill in order to improve mental workload and performance. The field of robotics has become very much focused on human-robot collaboration for applications such as, but not limited to, aviation and manufacturing.

Furthermore, both studies could inform the development of assistive technology. In particular, this work could inform our understanding of the cognitive-psycho-motor mechanisms in individuals with severe disabilities using various types of human-machine interfaces for rehabilitation. Additionally, understanding the relationship between performance, mental workload and psychological factors, such as efficacy beliefs, trust, and sense of attribution could greatly inform how different assistive technologies are developed. Beyond the development of assistive technology, training patients could be individualized with a greater understanding of this complex relationship, which characterizes human motor behavior.

Appendix A: Statistical results from spectral comparison of de-noising methods

Table 1: Main effects for spectral comparison of de-noising methods

Frequency	Main Effect of Method	*p*-value	Partial Eta Squared
Theta	$F(1.05, 17.79) = 54.55$	< 0.001	0.76
Low Alpha	$F(1.02, 17.36) = 63.83$	< 0.001	0.79
High Alpha	$F(1.07, 18.12) = 84.03$	< 0.001	0.83
Low Beta	$F(1.02, 17.41) = 121.36$	< 0.001	0.87
High Beta	$F(1.02, 17.36) = 61.40$	< 0.001	0.78

Table 2: Interactions and relevant post-hoc analysis for spectral comparison of de-noising methods

Frequency	Method X Region Interaction	*p*-value	Partial Eta Squared	Region	Comparison	*p*-value	Cohen's d
Theta	$F(2.47, 42.06) = 9.32$	< 0.001	0.35	F	M1 vs. M2	0.665	0.08
					M1 vs. M3	< 0.001	0.76
					M2 vs. M3	< 0.001	0.70
				C	M1 vs. M2	0.993	0.03
					M1 vs. M3	< 0.001	1.53
					M2 vs. M3	< 0.001	1.54
				T	M1 vs. M2	0.955	0.08
					M1 vs. M3	0.002	1.00
					M2 vs. M3	< 0.001	1.14
				P	M1 vs. M2	1.00	0.007
					M1 vs. M3	< 0.001	1.54
					M2 vs. M3	< 0.001	1.57
				O	M1 vs. M2	1.00	0.02
					M1 vs. M3	< 0.001	1.46
					M2 vs. M3	< 0.001	1.48
Low Alpha	$F(2.38, 40.50) = 9.10$	< 0.001	0.35	F	M1 vs. M2	0.784	0.20
					M1 vs. M3	< 0.001	1.73
					M2 vs. M3	< 0.001	1.57
				C	M1 vs. M2	0.98	0.08
					M1 vs. M3	< 0.001	1.88
					M2 vs. M3	< 0.001	1.86
				T	M1 vs. M2	0.947	0.12
					M1 vs. M3	< 0.001	1.62
					M2 vs. M3	< 0.001	1.75
				P	M1 vs. M2	1.00	0.02
					M1 vs. M3	< 0.001	2.07
					M2 vs. M3	< 0.001	2.08
				O	M1 vs. M2	1.00	0.01
					M1 vs. M3	< 0.001	2.13
					M2 vs. M3	< 0.001	2.13
High Alpha	$F(2.26, 38.42) = 9.44$	< 0.001	0.36	F	M1 vs. M2	0.511	0.36
					M1 vs. M3	< 0.001	1.99
					M2 vs. M3	< 0.001	1.40
				C	M1 vs. M2	0.954	0.17
					M1 vs. M3	< 0.001	2.47
					M2 vs. M3	< 0.001	2.39
				T	M1 vs. M2	0.988	0.08
					M1 vs. M3	< 0.001	2.26
					M2 vs. M3	< 0.001	2.34
				P	M1 vs. M2	1.00	0.002
					M1 vs. M3	< 0.001	2.36
					M2 vs. M3	< 0.001	2.37
				O	M1 vs. M2	0.999	0.03
					M1 vs. M3	< 0.001	2.22
					M2 vs. M3	< 0.001	2.24
Low Beta	$F(1.94, 33.01) = 3.61$	0.04	0.17	F	M1 vs. M2	0.772	0.463
					M1 vs. M3	< 0.001	2.59
					M2 vs. M3	< 0.001	2.25
				C	M1 vs. M2	0.989	0.12
					M1 vs. M3	< 0.001	2.72
					M2 vs. M3	< 0.001	2.71
				T	M1 vs. M2	0.999	0.02
					M1 vs. M3	< 0.001	1.33
					M2 vs. M3	< 0.001	1.34
				P	M1 vs. M2	1.00	0.02
					M1 vs. M3	< 0.001	2.69
					M2 vs. M3	< 0.001	2.74
				O	M1 vs. M2	0.996	0.06
					M1 vs. M3	< 0.001	2.00
					M2 vs. M3	< 0.001	2.02

Appendix B: NASA TLX

Figure 8.6

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 XXXX Research #	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

Appendix C: Self-efficacy survey

Survey

How confident are you that you can reach the targets as fast as possible?

0	10	20	30	40	50	60	70	80	90	100
Not at all confident					Moderately confident					Very confident

How confident are you that you can reach the targets as straight as possible?

0	10	20	30	40	50	60	70	80	90	100
Not at all confident					Moderately confident					Very confident

How confident are you that you can perform this reaching task well?

0	10	20	30	40	50	60	70	80	90	100
Not at all confident					Moderately confident					Very confident

Appendix D: Collective efficacy survey

Survey

How confident are you that your team can reach the targets as fast as possible?

0	10	20	30	40	50	60	70	80	90	100
Not at all confident					Moderately confident					Very confident

How confident are you that your team can reach the targets as straight as possible?

0	10	20	30	40	50	60	70	80	90	100
Not at all confident					Moderately confident					Very confident

How confident are you that your team can perform this reaching task well?

0	10	20	30	40	50	60	70	80	90	100
Not at all confident					Moderately confident					Very confident

Appendix E: Sense of attribution survey

1. How well do you feel you performed in this session? (Please circle one)

1	2	3	4	5
not well at all	not well	so-so	well	very well

2. How well do you feel your teammate performed in this session? (Please circle one)

1	2	3	4	5
not well at all	not well	so-so	well	very well

3. How well do you feel your team performed in this session? (Please circle one)

1	2	3	4	5
not well at all	not well	so-so	well	very well

4. What was the primary cause of the targets being reached as fast and as straight as possible?

Instructions: Think about the reason you have written on the previous page. The items below concern your impressions or opinions of this cause or causes of your team's outcome. Please circle one number for each of the following scales.

Is the cause(s) something:

1. That reflects an aspect of yourself	9	8	7	6	5	4	3	2	1	That reflects an aspect of your teammate
2. Caused by an aspect of your team	9	8	7	6	5	4	3	2	1	Caused by an aspect of the situation
3. Manageable by you	9	8	7	6	5	4	3	2	1	Manageable by your teammate
4. Your team can do something about	9	8	7	6	5	4	3	2	1	Your team can do nothing about
5. Permanent	9	8	7	6	5	4	3	2	1	Temporary
6. You can regulate	9	8	7	6	5	4	3	2	1	Your teammate can regulate
7. Your team can control	9	8	7	6	5	4	3	2	1	Your team cannot control
8. Over which others have control	9	8	7	6	5	4	3	2	1	Over which others have no control
9. Within you	9	8	7	6	5	4	3	2	1	Within your teammate
10. Within the team	9	8	7	6	5	4	3	2	1	Outside the team
11. That is stable over time	9	8	7	6	5	4	3	2	1	That varies over time
12. Under the power of other people	9	8	7	6	5	4	3	2	1	Not under the power of other people
13. Due to you	9	8	7	6	5	4	3	2	1	Due to your teammate
14. Due to your team	9	8	7	6	5	4	3	2	1	Due to factors outside your team
15. Over which you have power	9	8	7	6	5	4	3	2	1	Over which your teammate has power
16. Over which your team has power	9	8	7	6	5	4	3	2	1	Over which your team has no power
17. Unchangeable	9	8	7	6	5	4	3	2	1	Changeable
18. Other people can regulate	9	8	7	6	5	4	3	2	1	Other people cannot regulate

Appendix F: Trust survey

Survey

To what extent do you trust your teammate to reach the targets as fast as possible?

0 1 2 3 4 5 6 7 8 9 10

Not at all Completely

To what extent do you trust your teammate to reach the targets as straight as possible?

0 1 2 3 4 5 6 7 8 9 10

Not at all Completely

To what extent do you trust your teammate to perform this reaching task well?

0 1 2 3 4 5 6 7 8 9 10

Not at all Completely

Overall, how much do you trust your teammate?

0 1 2 3 4 5 6 7 8 9 10

Not at all Completely

Bibliography

Abo-Zahhad, M., Ahmed, S. M., & Abbas, S. N. (2015). A new EEG acquisition protocol for biometric identification using eye blinking signals. *International Journal of Intelligent Systems and Applications*, *7*(6), 48.

Akizuki, K., & Ohashi, Y. (2015). Measurement of functional task difficulty during motor learning: What level of difficulty corresponds to the optimal challenge point?. *Human movement science*, *43*, 107-117.

Allen, M. S., Jones, M. V., & Sheffield, D. (2009). Attribution, emotion, and collective efficacy in sports teams. *Group Dynamics: Theory, Research, and Practice*, *13*(3), 205.

Ayaz, H., Onaral, B., Izzetoglu, K., Shewokis, P. A., McKendrick, R., & Parasuraman, R. (2013). Continuous monitoring of brain dynamics with functional near infrared spectroscopy as a tool for neuroergonomic research: empirical examples and a technological development. *Frontiers in human neuroscience*, *7*.

Bailey, N. R., Scerbo, M. W., Freeman, F. G., Mikulka, P. J., & Scott, L. A. (2006). Comparison of a brain-based adaptive system and a manual adaptable system for invoking automation. *Human factors*, *48*(4), 693-709.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. Macmillan.

Bandura, A. (2006). Guide for constructing self-efficacy scales. *Self-efficacy beliefs of adolescents*, *5*(307-337).

Barry, R. J., Steiner, G. Z., & De Blasio, F. M. (2016). Reinstating the novelty P3. *Scientific reports*, *6*, 31200.

Boonstra, T. W., Daffertshofer, A., Breakspear, M., & Beek, P. J. (2007). Multivariate time–frequency analysis of electromagnetic brain activity during bimanual motor learning. *Neuroimage*, *36*(2), 370-377.

Bradford, J. C., Lukos, J. R., Passaro, A., Ries, A., & Ferris, D. P. (2019). Effect of locomotor demands on cognitive processing. *Scientific reports*, *9*(1), 1-12.

Bray, C. D., & Whaley, D. E. (2001). Team cohesion, effort, and objective individual performance of high school basketball players. *The Sport Psychologist*, *15*(3), 260-275.

Broad, A., Schultz, J., Derry, M., Murphey, T., & Argall, B. (2017). Trust adaptation leads to lower control effort in shared control of crane automation. *IEEE Robotics and Automation Letters*, *2*(1), 239-246.

Bursztyn, L. L., Ganesh, G., Imamizu, H., Kawato, M., & Flanagan, J. R. (2006). Neural correlates of internal-model loading. *Current Biology*, *16*(24), 2440-2445.

Card, S. K., Mackinlay, J. D., & Robertson, G. G. (1991). A morphological analysis of the design space of input devices. *ACM Transactions on Information Systems (TOIS)*, *9*(2), 99-122.

Carron, A. V., Bray, S. R., & Eys, M. A. (2002). Team cohesion and team success in sport. *Journal of sports sciences*, *20*(2), 119-126.

Carron, A. V., Colman, M. M., Wheeler, J., & Stevens, D. (2002). Cohesion and performance in sport: A meta analysis. *Journal of Sport and Exercise Psychology*, *24*(2), 168-188.

Casadio, M., Ranganathan, R., & Mussa-Ivaldi, F. A. (2012). The body-machine interface: a new perspective on an old theme. *Journal of Motor behavior*, *44*(6), 419-433.

Chen, G., Bliese, P. D., Payne, S. C., Zaccaro, S. J., Simsarian Webber, S., Mathieu, J. E., & Born, D. H. (2002). Simultaneous examination of the antecedents and consequences of efficacy beliefs at multiple levels of analysis. *Human Performance*, *15*(4), 381-409.

Chou, H. W., Lin, Y. H., Chang, H. H., & Chuang, W. W. (2013). Transformational leadership and team performance: The mediating roles of cognitive trust and collective efficacy. *Sage Open*, *3*(3), 2158244013497027.

Chow, G. M., & Feltz, D. L. (2008). Exploring the relationships between collective efficacy, perceptions of success, and team attributions. *Journal of sports sciences*, *26*(11), 1179-1189.

Chwalisz, K., Altmaier, E. M., & Russell, D. W. (1992). Causal attributions, self-efficacy cognitions, and coping with stress. *Journal of social and clinical psychology*, *11*(4), 377-400.

Clark, R. E. (1999). Yin and yang cognitive motivational processes operating in multimedia learning environments. *Cognition and multimedia design*, 73-107.

Cook, R. D., & Weisberg, S. (1982). *Residuals and influence in regression*. New York: Chapman and Hall.

Daly, I., Billinger, M., Scherer, R., & Müller-Putz, G. (2013). On the automated removal of artifacts related to head movement from the EEG. *IEEE Transactions on neural systems and rehabilitation engineering*, *21*(3), 427-434.

de Visser, E. J., Beatty, P. J., Estepp, J. R., Kohn, S., Abubshait, A., Fedota, J. R., & McDonald, C. G. (2018). Learning from the slips of others: Neural correlates of trust in automated agents. *Frontiers in human neuroscience*, *12*, 309.

DeWolf, T., Stewart, T. C., Slotine, J. J., & Eliasmith, C. (2016). A spiking neural model of adaptive arm control. *Proceedings of the Royal Society B: Biological Sciences*, *283*(1843), 20162134.

Dirks, K. T. (1999). The effects of interpersonal trust on work group performance. *Journal of applied psychology*, *84*(3), 445.

Dyke, F. B., Leiker, A. M., Grand, K. F., Godwin, M. M., Thompson, A. G., Rietschel, J. C., ... & Miller, M. W. (2015). The efficacy of auditory probes in indexing cognitive workload is dependent on stimulus complexity. *International Journal of Psychophysiology*, *95*(1), 56-62.

Ede, A., Sullivan, P. J., & Feltz, D. L. (2017). Self-doubt: Uncertainty as a motivating factor on effort in an exercise endurance task. *Psychology of Sport and Exercise*, *28*, 31-36.

Erdem, F., & Ozen, J. (2003). Cognitive and affective dimensions of trust in developing team performance. *Team Performance Management: An International Journal*, *9*(5/6), 131-135.

Fabiani, M., Kazmerski, V. A., Cycowicz, Y. M., & Friedman, D. (1996). Naming norms for brief environmental sounds: Effects of age and dementia. *Psychophysiology*, *33*(4), 462-475.

Feltz, D. L., & Lirgg, C. D. (1998). Perceived team and player efficacy in hockey. *Journal of applied psychology*, *83*(4), 557.

Feltz, D. L., Forlenza, S. T., Winn, B., & Kerr, N. L. (2014). Cyber buddy is better than no buddy: a test of the köhler motivation effect in exergames. *GAMES FOR HEALTH: Research, Development, and Clinical Applications*, *3*(2), 98-105.

Feltz, D. L., Ploutz-Snyder, L., Winn, B., Kerr, N. L., Pivarnik, J. M., Ede, A., Hill, C., Samendinger, S., & Jeffery, W. (2016). Simulated Partners and Collaborative Exercise (SPACE) to boost motivation for astronauts: study protocol. *BMC psychology*, *4*(1), 54.

Funke, G. J., Knott, B. A., Salas, E., Pavlas, D., & Strang, A. J. (2012). Conceptualization and measurement of team workload: A critical need. *Human Factors*, *54*(1), 36-51.

Funke, G. J., Warm, J. S., Baldwin, C. L., Garcia, A., Funke, M. E., Dillard, M. B., Finmore, V.S., Matthews, G., & Greenlee, E. T. (2016). The independence and interdependence of coacting observers in regard to performance efficiency, workload, and stress in a vigilance task. *Human factors*, *58*(6), 915-926.

Gentili, R. J., Bradberry, T. J., Oh, H., Hatfield, B. D., & Contreras Vidal, J. L. (2011). Cerebral cortical dynamics during visuomotor transformation:

Adaptation to a cognitive-motor executive challenge. *Psychophysiology*, *48*(6), 813-824.

Gentili, R. J., Shewokis, P. A., Ayaz, H., & Contreras-Vidal, J. L. (2013). Functional near-infrared spectroscopy-based correlates of prefrontal cortical dynamics during a cognitive-motor executive adaptation task. *Frontiers in human neuroscience*, *7*.

Gentili, R. J., Rietschel, J. C., Jaquess, K. J., Lo, L. C., Prevost, C. M., Miller, M. W., Mohler, J.M., Oh, H., Tan, Y.Y., & Hatfield, B. D. (2014, August). Brain biomarkers based assessment of cognitive workload in pilots under various task demands. In *Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE* (pp. 5860-5863). IEEE.

Gentili, R. J., Bradberry, T. J., Oh, H., Costanzo, M. E., Kerick, S. E., Contreras-Vidal, J. L., & Hatfield, B. D. (2015). Evolution of cerebral cortico-cortical communication during visuomotor adaptation to a cognitive-motor executive challenge. *Biological psychology*, *105*, 51-65.

Gentili, R. J., Jaquess, K. J., Shuggi, I. M., Shaw, E. P., Oh, H., Lo, L. C., Tan, Y.Y., Domingues, C.A., Blanco, J.A., Rietschel, J.C., Miller, M. W., & Hatfield, B.D. (2018). Combined assessment of attentional reserve and cognitive‐motor effort under various levels of challenge with a dry EEG system. *Psychophysiology*, *55*(6), e13059.

Gevins, A., Smith, M. E., McEvoy, L., & Yu, D. (1997). High-resolution EEG mapping of cortical activation related to working memory: effects of task difficulty, type of processing, and practice. *Cerebral cortex (New York, NY: 1991)*, *7*(4), 374-385.

Gevins, A., & Smith, M. E. (2000). Neurophysiological measures of working memory and individual differences in cognitive ability and cognitive style. *Cerebral cortex*, *10*(9), 829-839.

Gevins, A., & Smith, M. E. (2003). Neurophysiological measures of cognitive workload during human-computer interaction. *Theoretical Issues in Ergonomics Science*, *4*(1-2), 113-131.

Goil, A., Derry, M., & Argall, B. D. (2013, June). Using machine learning to blend human and robot controls for assisted wheelchair navigation. In *Rehabilitation Robotics (ICORR), 2013 IEEE International Conference on*(pp. 1-6). IEEE.

Greenlees, I., Lane, A., Thelwell, R., Holder, T., & Hobson, G. (2005). Team-referent attributions among sport performers. *Research Quarterly for Exercise and Sport*, *76*(4), 477-487.

Guadagnoli, M. A., & Lee, T. D. (2004). Challenge point: a framework for conceptualizing the effects of various practice conditions in motor learning. *Journal of motor behavior*, *36*(2), 212-224.

Guastello, S. J., Shircel, A., Malon, M., & Timm, P. (2015). Individual differences in the experience of cognitive workload. *Theoretical Issues in Ergonomics Science*, *16*(1), 20-52.

Harriott, C. E., Buford, G. L., Adams, J. A., & Zhang, T. (2015). Mental workload and task performance in peer-based human-robot teams. *Journal of Human-Robot Interaction*, *4*(2), 61-96.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. *Advances in psychology*, *52*, 139-183.

Hart, S. G. (2006, October). NASA-task load index (NASA-TLX); 20 years later. In *Proceedings of the human factors and ergonomics society annual meeting* (Vol. 50, No. 9, pp. 904-908). Sage CA: Los Angeles, CA: Sage Publications.

Hatfield, B. D., Costanzo, M. E., Goodman, R. N., Lo, L. C., Oh, H., Rietschel, J. C., Saffer, M., Bradberry, T., Contreras-Vidal, J., & Haufler, A. (2013). The influence of social evaluation on cerebral cortical activity and motor performance: A study of "Real-Life" competition. *International Journal of Psychophysiology*, *90*(2), 240-249.

Helton, W. S., Funke, G. J., & Knott, B. A. (2014). Measuring workload in collaborative contexts: trait versus state perspectives. *Human factors*, *56*(2), 322-332.

Hilburn, B., Jorna, P. G., Byrne, E. A., & Parasuraman, R. (1997). The effect of adaptive air traffic control (ATC) decision aiding on controller mental workload. *Human-automation interaction: Research and practice*, 84-91.

Hu, J. S., Lu, J., Tan, W. B., & Lomanto, D. (2016). Training improves laparoscopic tasks performance and decreases operator workload. *Surgical endoscopy*, *30*(5), 1742-1746.

Hu, W. L., Akash, K., Jain, N., & Reid, T. (2016). Real-Time Sensing of Trust in Human-Machine Interactions. *IFAC-PapersOnLine*, *49*(32), 48-53.

Ishii, R., Canuet, L., Ishihara, T., Aoki, Y., Ikeda, S., Hata, M., Katsimichas, T., Gunji, A., Takahashi, H., Nakahachi, T., Iwase, M., & Takeda, M. (2014). Frontal midline theta rhythm and gamma power changes during focused attention on mental calculation: an MEG beamformer analysis. *Frontiers in human neuroscience*, *8*, 406.

Jackson, B., Grove, J. R., & Beauchamp, M. R. (2010). Relational efficacy beliefs and relationship quality within coach-athlete dyads. *Journal of Social and Personal Relationships*, *27*(8), 1035-1050.

Jagacinski, R. J., & Monk, D. L. (1985). Fitts' Law in Two dimensions with hand and head movements movements. *Journal of Motor Behavior*, *17*(1), 77-95.

Jaquess, K. J., Gentili, R. J., Lo, L. C., Oh, H., Zhang, J., Rietschel, J. C., Miller, M.W., Tan, Y.Y., & Hatfield, B. D. (2017). Empirical evidence for the relationship between cognitive workload and attentional reserve. *International Journal of Psychophysiology*, *121*, 46-55.

Jaquess, K. J., Lo, L. C., Oh, H., Lu, C., Ginsberg, A., Tan, Y. Y., Lohse, K.R., Miller, M.W., Hatfied, B.D., & Gentili, R. J. (2018). Changes in mental workload and motor performance throughout multiple practice sessions under various levels of task difficulty. *Neuroscience*, *393*, 305-318.

Kaber, D. B., & Endsley, M. R. (2004). The effects of level of automation and adaptive automation on human performance, situation awareness and workload in a dynamic control task. *Theoretical Issues in Ergonomics Science*, *5*(2), 113-153.

Kanfer, R., & Ackerman, P. L. (1989). Motivation and cognitive abilities: An integrative/aptitude-treatment interaction approach to skill acquisition. *Journal of applied psychology*, *74*(4), 657.

Kanfer, R., & Kanfer, F. H. (1991). Goals self-regulation: Applications or theory to work settings'. *ML Maehr and PR Pintrich (edn), Advances in Motivation and Achievement vol, JAI Press, Greenwich, CT*, 287-326.

Kantak, S. S., & Winstein, C. J. (2012). Learning–performance distinction and memory processes for motor skills: A focused review and perspective. *Behavioural brain research*, *228*(1), 219-231.

Karoly, P. (1993). Mechanisms of self-regulation: A systems view. *Annual review of psychology*, *44*(1), 23-52.

Ke, Y., Qi, H., He, F., Liu, S., Zhao, X., Zhou, P., Zhang, L., & Ming, D. (2014). An EEG-based mental workload estimator trained on working memory task can work well under simulated multi-attribute task. *Frontiers in human neuroscience*, *8*.

Kerick, S. E., Douglass, L. W., & Hatfield, B. D. (2004). Cerebral cortical adaptations associated with visuomotor practice. *Medicine & Science in Sports & Exercise*.

Khatun, S., Morshed, B. I., & Bidelman, G. M. (2018, May). Single Channel EEG Based Score Generation to Monitor the Severity and Progression of Mild Cognitive Impairment. In *2018 IEEE International Conference on Electro/Information Technology (EIT)* (pp. 0882-0886). IEEE.

Kim, B. H., Chun, J., & Jo, S. (2015, April). Dynamic motion artifact removal using inertial sensors for mobile BCI. In *Neural Engineering (NER), 2015 7th International IEEE/EMBS Conference on* (pp. 37-40). IEEE.

Kirschner, F., Paas, F., & Kirschner, P. A. (2009). A cognitive load approach to collaborative learning: United brains for complex tasks. *Educational Psychology Review*, *21*(1), 31-42.

Kitazawa, S., Goto, T., Urushihara, Y. (1993). Quantitative evaluation of reaching movements in cats with and without cerebellar lesions using normalized integral of jerk. *Role of the cerebellum and basal ganglia in voluntary movement* 11–19.

Kline, J. E., Huang, H. J., Snyder, K. L., & Ferris, D. P. (2015). Isolating gait-related movement artifacts in electroencephalography during human walking. *Journal of neural engineering*, *12*(4), 046022.

Lau, C., & O'Leary, S. (1993). Comparison of computer interface devices for persons with severe physical disabilities. *American Journal of Occupational Therapy*, *47*(11), 1022-1030.

Lay, B. S., Sparrow, W. A., Hughes, K. M., & O'Dwyer, N. J. (2002). Practice effects on coordination and control, metabolic energy expenditure, and muscle activation. *Human movement science*, *21*(5-6), 807-830.

Luck, S. J. (2014). *An introduction to the event-related potential technique*. MIT press.

Marcos, F. M. L., Miguel, P. A. S., Oliva, D. S., & Calvo, T. G. (2010). Interactive effects of team cohesion on perceived efficacy in semi-professional sport. *Journal of sports science & medicine*, *9*(2), 320.

Maynard, M. T., Kennedy, D. M., & Sommer, S. A. (2015). Team adaptation: A fifteen-year synthesis (1998–2013) and framework for how this literature needs to "adapt" going forward. *European Journal of Work and Organizational Psychology*, *24*(5), 652-677.

McAllister, D. J. (1995). Affect-and cognition-based trust as foundations for interpersonal cooperation in organizations. *Academy of management journal*, *38*(1), 24-59.

McAuley, E., Duncan, T. E., & Russell, D. W. (1992). Measuring causal attributions: The revised causal dimension scale (CDSII). *Personality and Social Psychology Bulletin*, *18*(5), 566-573.

Miller, M. W., Rietschel, J. C., McDonald, C. G., & Hatfield, B. D. (2011). A novel approach to the physiological measurement of mental workload. *International Journal of Psychophysiology*, *80*(1), 75-78.

Miller, M. W., Groman, L. J., Rietschel, J. C., McDonald, C. G., Iso-Ahola, S. E., & Hatfield, B. D. (2013). The effects of team environment on attentional resource allocation and cognitive workload. *Sport, Exercise, and Performance Psychology*, *2*(2), 77.

Miller, M. W., Presacco, A., Groman, L. J., Bur, S., Rietschel, J. C., Gentili, R. J., McDonald, C.G., Iso-Ahola, S.E., & Hatfield, B. D. (2014). The effects of team environment on cerebral cortical processes and attentional reserve. *Sport, Exercise, and Performance Psychology*, *3*(1), 61.

Moisello, C., Blanco, D., Lin, J., Panday, P., Kelly, S. P., Quartarone, A., Di Rocco, A., Cirelli, C., Tononi, G., & Ghilardi, M. F. (2015). Practice changes beta power at rest and its modulation during movement in healthy subjects but not in patients with P arkinson's disease. *Brain and behavior*, *5*(10), e00374.

Moray, N., Inagaki, T., & Itoh, M. (2000). Adaptive automation, trust, and self-confidence in fault management of time-critical tasks. *Journal of experimental psychology: Applied*, *6*(1), 44.

Mussa-Ivaldi, F. A., Casadio, M., Danziger, Z. C., Mosier, K. M., & Scheidt, R. A. (2011). Sensory motor remapping of space in human–machine interfaces. *Progress in brain research*, *191*, 45.

Muthukumaraswamy, S. (2013). High-frequency brain activity and muscle artifacts in MEG/EEG: a review and recommendations. *Frontiers in human neuroscience*, *7*, 138.

Myers, N. D., Payment, C. A., & Feltz, D. L. (2004). Reciprocal relationships between collective efficacy and team performance in women's ice hockey. *Group Dynamics*, *8*, 182-195.

Oldfield, R. C. (1971). The assessment and analysis of handedness: the Edinburgh inventory. *Neuropsychologia*, *9*(1), 97-113.

Onikura, K., Katayama, Y., & Iramina, K. (2015). Evaluation of a method of removing head movement artifact from EEG by independent component analysis and filtering. *Advanced Biomedical Engineering*, *4*, 67-72.

Paas, F. G., & Van Merriënboer, J. J. (1994). Variability of worked examples and transfer of geometrical problem-solving skills: A cognitive-load approach. *Journal of educational psychology*, *86*(1), 122.

Paas, F., Tuovinen, J. E., Tabbers, H., & Van Gerven, P. W. (2003). Cognitive load measurement as a means to advance cognitive load theory. *Educational psychologist*, *38*(1), 63-71.

Paas, F., Van Gog, T., & Sweller, J. (2010). Cognitive load theory: New conceptualizations, specifications, and integrated research perspectives. *Educational Psychology Review*, *22*(2), 115-121.

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human factors*, *39*(2), 230-253.

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on systems, man, and cybernetics-Part A: Systems and Humans*, *30*(3), 286-297.

Parasuraman, R., Barnes, M., Cosenzo, K., & Mulgund, S. (2007). *Adaptive automation for human-robot teaming in future command and control systems*. ARMY RESEARCH LAB ABERDEEN PROVING GROUND MD HUMAN RESEARCH AND ENGINEERING DIRECTORATE.

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2008). Situation awareness, mental workload, and trust in automation: Viable, empirically supported cognitive engineering constructs. *Journal of cognitive engineering and decision making*, *2*(2), 140-160.

Perfetti, B., Moisello, C., Landsness, E. C., Kvint, S., Lanzafame, S., Onofrj, M., Di Rocco, A., Tononi, G., & Ghilardi, M. F. (2011). Modulation of gamma and theta spectral amplitude and phase synchronization is associated with the development of visuo-motor learning. *Journal of Neuroscience*, *31*(41), 14810-14819.

Polich, J. (2007). Updating P300: an integrative theory of P3a and P3b. *Clinical neurophysiology*, *118*(10), 2128-2148.

Pollok, B., Latz, D., Krause, V., Butz, M., & Schnitzler, A. (2014). Changes of motor-cortical oscillations associated with motor learning. *Neuroscience*, *275*, 47-53.

Rietschel, J. C., Goodman, R. N., King, B. R., Lo, L. C., Contreras‐Vidal, J. L., & Hatfield, B. D. (2011). Cerebral cortical dynamics and the quality of motor behavior during social evaluative challenge. *Psychophysiology*, *48*(4), 479-487.

Rietschel, J. C., Miller, M. W., Gentili, R. J., Goodman, R. N., McDonald, C. G., & Hatfield, B. D. (2012). Cerebral-cortical networking and activation increase as a function of cognitive-motor task difficulty. *Biological psychology*, *90*(2), 127-133.

Rietschel, J. C., McDonald, C. G., Goodman, R. N., Miller, M. W., Jones-Lush, L. M., Wittenberg, G. F., & Hatfield, B. D. (2014). Psychophysiological support of increasing attentional reserve during the development of a motor skill. *Biological psychology*, *103*, 349-356.

Saavedra, R., Earley, P. C., & Van Dyne, L. (1993). Complex interdependence in task-performing groups. *Journal of applied psychology*, *78*(1), 61.

Scheer, M., Bülthoff, H. H., & Chuang, L. L. (2016). Steering demands diminish the early-P3, late-P3 and RON components of the event-related potential of task-irrelevant environmental sounds. *Frontiers in human neuroscience*, *10*, 73.

Schneider, W., & Shiffrin, R. M. (1977). Controlled and automatic human information processing: I. Detection, search, and attention. *Psychological review*, *84*(1), 1.

Sellers, J., Helton, W. S., Näswall, K., Funke, G. J., & Knott, B. A. (2014, September). Development of the team workload questionnaire (TWLQ). In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*(Vol. 58, No. 1, pp. 989-993). Sage CA: Los Angeles, CA: SAGE Publications.

Shaw, E. P., Rietschel, J. C., Hendershot, B. D., Pruziner, A. L., Miller, M. W., Hatfield, B. D., & Gentili, R. J. (2018). Measurement of attentional reserve and mental effort for cognitive workload assessment under various task demands during dual-task walking. *Biological psychology*, *134*, 39-51.

Shea, C. H., Wulf, G., & Whitacre, C. (1999). Enhancing training efficiency and effectiveness through the use of dyad training. *Journal of motor behavior*, *31*(2), 119-125.

Shea, C. H., Wright, D. L., Wulf, G., & Whitacre, C. (2000). Physical and observational practice afford unique learning opportunities. *Journal of motor behavior*, *32*(1), 27-36.

Shebilskem, W. L., Regian, J. W., Arthur Jr, W., & Jordan, J. A. (1992). A dyadic protocol for training complex skills. *Human Factors*, *34*(3), 369-374.

Sheridan, T. B. (2002). *Humans and automation: System design and research issues*. John Wiley & Sons, Inc.

Shewokis, P. A., Ayaz, H., Panait, L., Liu, Y., Syed, M., Greenawald, L., Shariff, F.U., Castellanos, A., & Lind, D. S. (2015, August). Brain-in-the-Loop learning using fNIR and simulated virtual reality surgical tasks: hemodynamic and behavioral effects. In *International Conference on Augmented Cognition* (pp. 324-335). Springer, Cham.

Shuggi, I. M., Oh, H., Shewokis, P. A., & Gentili, R. J. (2017). Mental workload and motor performance dynamics during practice of reaching movements under various levels of task difficulty. *Neuroscience*, *360*, 166-179.

Shuggi, I. M., Shewokis, P. A., Herrmann, J.W., & Gentili, R. J. (2018). Changes in motor performance and mental workload during learning of reaching movements: a team dynamics perspective. *Experimental Brain Research*, *236*(2), 433-451.

Shuggi, I. M., Oh, H., Wu, H., Ayoub, M. J., Moreno, A., Shaw, E. P., Shewokis, P.A., & Gentili, R. J. (2019). Motor performance, mental workload and self-efficacy dynamics during learning of reaching movements throughout multiple practice sessions. *Neuroscience*, *423*, 232-248.

Stajkovic, A. D., Lee, D., & Nyberg, A. J. (2009). Collective efficacy, group potency, and group performance: meta-analyses of their relationships, and test of a mediation model. *Journal of applied psychology*, *94*(3), 814.

Stevens, R., Berka, C., & Sprang, M. (2009, October). Neurophysiologic collaboration patterns during team problem solving. In *Proceedings of the human factors and ergonomics Society annual meeting* (Vol. 53, No. 12, pp. 804-808). Sage CA: Los Angeles, CA: SAGE Publications.

Stevens, R. H., Galloway, T. L., Wang, P., & Berka, C. (2012). Cognitive neurophysiologic synchronies: What can they contribute to the study of teamwork?. *Human factors*, *54*(4), 489-502.

Thompson, J. D. (1967). *Organizations in action: Social science bases of administrative theory*. Transaction publishers.

Trope, Y. (1983). Self-assessment in achievement behavior. In *Psychological perspectives on the self*. Erlbaum.

Van de Ven, A. H., Delbecq, A. L., & Koenig Jr, R. (1976). Determinants of coordination modes within organizations. *American sociological review*, 322-338.

Van Gog, T., & Paas, F. (2008). Instructional efficiency: Revisiting the original construct in educational research. *Educational Psychologist*, *43*(1), 16-26.

Warner, S., Bowers, M. T., & Dixon, M. A. (2012). Team dynamics: A social network perspective. *Journal of Sport Management*, *26*(1), 53-66.

Weber, E., & Doppelmayr, M. (2016). Kinesthetic motor imagery training modulates frontal midline theta during imagination of a dart throw. *International journal of Psychophysiology*, *110*, 137-145.

Weiner, B., Russell, D., & Lerman, D. (1979). The cognition–emotion process in achievement-related contexts. *Journal of Personality and Social psychology*, *37*(7), 1211.

Weiner, B. (1985). An attributional theory of achievement motivation and emotion. *Psychological Review, 92*(4), 548-573.

Wickens, C. D. (2002). Multiple resources and performance prediction. *Theoretical issues in ergonomics science*, *3*(2), 159-177.

Wickens, C. D. (2008). Multiple resources and mental workload. *Human factors*, *50*(3), 449-455.

Wiener, E. L. (1988). Cockpit automation. *Human Factors in Aviation*, 433-461.

Williams, M. R., & Kirsch, R. F. (2008). Evaluation of head orientation and neck muscle EMG signals as command inputs to a human–computer interface for individuals with high tetraplegia. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *16*(5), 485-496.

Williams, M. R., & Kirsch, R. F. (2015). Evaluation of head orientation and neck muscle EMG signals as three-dimensional command sources. *Journal of neuroengineering and rehabilitation*, *12*(1), 25.

Wulf, G., Shea, C., & Lewthwaite, R. (2010). Motor skill learning and performance: a review of influential factors. *Medical education*, *44*(1), 75-84.

You, S. and Robert, L. P. (2017). A Working Framework for Human-Robot Teamwork accepted to the Robots in Groups and Teams Workshop at 20th ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW 2017), Portland OR.

Young, M. S., Brookhuis, K. A., Wickens, C. D., & Hancock, P. A. (2015). State of science: mental workload in ergonomics. *Ergonomics*, *58*(1), 1-17.

Zheng, B., Jiang, X., Tien, G., Meneghetti, A., Panton, O. N. M., & Atkins, M. S. (2012). Workload assessment of surgeons: correlation between NASA TLX and blinks. *Surgical endoscopy*, *26*(10), 2746-2750.