Examining Neuroplasticity as a Function of Errors During Motor Learning

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~श्रीमद्भगवद्गीता[1]

[1] As a kindled fire reduces wood to ashes, so does the fire of knowledge burn to ashes all reactions from material activities.

Abstract

Proficient motor learning is important for both athletes looking to improve their performance and patients learning daily living skills. Research has identified different methods for learning motor skills, focusing on two types: implicit and explicit learning. Implicit learning happens with little awareness, while explicit learning requires more conscious thought. Studies show that implicit learning is often more effective because it uses less mental effort and is more reliable under stress. This might be due to stronger neural connections in the brain formed during implicit learning. However, it is unclear whether implicit learning leads to more brain changes, known as neuroplasticity, than explicit learning. Neuroplasticity is the brain's ability to adapt and form new memory networks in response to experiences. This study aims to investigate differences in neuroplastic changes resulting from implicit versus explicit learning of a traditional Dutch shuffleboard game (Sjoelbak). We used baseline electroencephalography (EEG) to measure changes in brain activity before and after practice to assess neuroplasticity. We examined the effects of errorless and errorful learning protocols on task performance and neural connectivity. Both strategies improved accuracy from pretest to posttest, indicating effective skill acquisition. However, participants struggled to transfer skills to new contexts, as shown by decreased performance in the transfer test. Despite expectations of greater neuroplastic changes as a function of errorless learning, resting-state beta connectivity analyses showed no significant interactions. However, no significant differences were evident in the overall error rates between the groups during the learning phase, suggesting that implicit motor learning may not have occurred for the errorless learning condition. This suggests that neural adaptations are more complex than initially hypothesized.

Chapter Overview

Chapter 1 provides an overview of the project's general details, exploring the relationship between neuroplasticity, working memory, and the two types of motor learning, as well as their connections to motor performance. This chapter summarizes existing research and outlines future directions in the field. It presents foundational aspects of the study, including a comprehensive literature review on skill learning, its historical context, theoretical underpinnings, and variations.

Additionally, the chapter discusses the emergence of working memory, its theoretical framework, and its relationship to distinct types of skill learning. It examines the merits and drawbacks of various motor learning approaches, their acquisition processes, and their correlation with working memory and brain adaptability. The chapter also highlights how different skill learning protocols influence neuroplasticity and addresses methods for differentiating the assessment of implicit and explicit learning in relation to plasticity.

Chapter 2 discusses the use of electroencephalography to assess neuroplasticity and discusses the relevance of electroencephalography for detecting neuroplastic changes in research subjects. It also highlights key brain regions associated with neuroplasticity, along with the methods and indicators used in this research and summarizes the key background to the study.

Chapter 3 provides a detailed account of the methodology employed for both implicit and explicit learning protocols, outlining the experimental procedures and specifications, along with the equipment used throughout the study.

Chapters 4 presents the findings, including the strategy used for statistical analysis, the error rate analysis during the practice sessions, performance analysis of the pretest, posttest and transfer test,

and the resting state beta connectivity analysis for the primary motor cortex and the superior temporal gyrus.

Chapter 5 discusses the findings in the context of implicit and explicit learning protocols and their significance for brain plasticity. Neither the errorless nor the errorful protocols demonstrated a significant influence on brain plasticity, it also discusses the limitations and future scope of the study.

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Chapter 1: Literature Review

1.1. General Introduction

Memory is a fundamental cognitive function that enables the storage of information related to everyday activities for both short-term and long-term durations. Throughout a person's life, new memories are continuously formed and can be replaced, updated, or altered over time. Each new memory leads to changes in the structure and function of nerve cells and synapses in the brain, illustrating the brain's plasticity. This malleability allows individuals to learn new skills, which, once consolidated into long-term memory, can be recalled, and utilized as needed.

A fundamental stance of this thesis is that skills can be learned through two primary methods: explicit and implicit learning. Explicit learning involves conscious awareness and effort, while implicit learning occurs without awareness and is less affected by age or cognitive constraints. Cognitive load, such as fatigue, can influence the learning process; for instance, under stressful conditions, individuals may rely more on explicit strategies. This suggests that implicit strategies could be more effective for skill acquisition, as they utilize fewer cognitive resources and may enhance neuro-adaptability.

Historically, explicit learning has dominated rehabilitation strategies, which can be slow, fatiguing, and effortful—and are particularly challenging for individuals facing cognitive difficulties. In contrast, implicit learning is often more intuitive, less tiring, and has greater retention capabilities. For example, in the context of rehabilitation for individuals relearning activities of daily living

(ADLs), implicit learning may facilitate quicker acquisition of skills, promoting independence (Orrell et al., 2009).

Research supports the view that skill learning can involve both explicit and implicit processes (Masters, 1992). Implicit learning is suggested to be more effective for long-term skill acquisition. Implicit learning encourages the accumulation of knowledge that is not available for conscious consideration. This knowledge tends to result in performance that is intuitive and operates independently of awareness, memory, and age constraints. Explicit learning, on the other hand, results in accumulation of knowledge that is available for conscious consideration. The knowledge can be reported as learning conditions became more stressful, individuals were more likely to rely on explicit knowledge and strategies. If this is true, it could improve skill acquisition in both sports and rehabilitation settings. However, even though the benefits of implicit learning for skill acquisition are becoming more recognized, there has been little research on how it relates to neuroplasticity.

This research aims to investigate whether implicit motor learning, induced by an errorless learning approach, results in greater differences in neuroplasticity than explicit motor learning induced by an errorful learning approach. The study will analyze brain activity patterns using electroencephalography (EEG) and evaluate the amount of motor learning using retention tests and transfer tests. This approach seeks to deepen our understanding of how different learning strategies impact neuroplasticity and skill acquisition.

1.2. Defining Skill

Lay definitions of skill often describe it simply as the "ability to do something." In contrast, researchers define skill as goal-oriented movements that are learned and require coordination of

various body systems (including central integration) (Morris & Whiting, 1971). Skill learning begins in infancy and continues to develop with age and increasing functional demands. Over time, humans acquire a vast pool of skills, influenced by both cognitive development and demands for environmental adaptability.

In younger individuals, for whom there is ongoing development of the brain, skills are acquired very rapidly, which allows them to readily learn basic movements, understand abstract concepts, and deal with new challenges. However, this responsiveness tends to decline in older adults due to cognitive decline, delayed responses, and reduced exposure to new goals (Light et al., 1990).

According to Systems Theory (Shi et al., 2011; Shumway-Cook, 2007), acquiring coordinated movement (i.e., skills) requires multiple systems to work in harmony, including the brain, which organizes and integrates vast amounts of sensory information. This concept was initially articulated by Morris and Whiting (1971), who noted that learning begins with the receiving cues from both internal and external environmental inputs, such as visuo-auditory and proprioceptive signals. These signals are processed by sensory and perceptual systems, which link the received information to memories of similar cues, enabling efficient output. The instructions from these systems are then translated into output commands that are sent to the effectors (muscles) for task execution. These foundational findings have influenced research on motor skill acquisition and led to various theories that examine the learning process, the systems involved in the learning process, and how to improve learning skills.

1.3. Theoretical Basis of Skill Learning

The process of skill acquisition has been debated for a long time, with some experts seeing it as a behavioral process and others as a response to environmental needs. Motor learning, or skill

learning, refers to acquiring movement for specific purposes, which is guided by the central nervous system (CNS).

Several theoretical frameworks have emerged to explain motor learning, with Adam's Closed Loop Theory (Adams, 1971) being one of the earliest. This theory suggests that learning happens through perceptual tracing, where the CNS compares sensory input with stored memories to correct errors during tasks. While it explains how linear and slow tasks are learned via memory recall, it does not fully account for rapid, non-linear learning or learning without sensory input, like verbal or visual cues.

In response to these limitations, Schmidt (1975) expanded upon Adam's theory by proposing Schema Theory. This model centers on the concept of "schema," defined as a rule, concept, or relationship formed through experience. This theory states that people learn skills by understanding how their bodies work and connecting muscle movements, actions, and sensations. Schmidt identified four key pieces of information that transform from short-term memory to procedural memory: Initial Conditions (IC), or body position before a task; Correlation of Movement (COM), which relates to similarities between tasks; Movement Outcome (MO), assessing how well the task was done; and Sensory Output (SO), which includes feedback during and after the task. The theory also distinguishes between recall that is based on past IC and MO, and recognition, which involves all four categories. While Schema Theory emphasizes the role of practice in skill learning and adapting to different environments, it does not fully explain how schemas form or how cognitive factors and environmental constraints affect performance. Also, according to Schmidt and Lee (2011), motor learning transcends mere practice; it is a complex phenomenon that encompasses various layers of neural organization, including temporal, spatial, and hierarchical structures. This complexity is evident in how motor learning alters the

mechanisms of perceptual learning, mediated by experience and training. It is a multi-dimensional process that involves changes in neural substrates, sensory integration, and adaptation to external influences. Furthermore, motor learning is dynamic and is characterized by the reorganization and refinement of movement abilities.

Stage models of skill learning have been proposed to try to describe some of the changes that occur during skill learning. For example, Fitts and Posner (1967) proposed a stepwise model of motor skill learning, outlining three stages: the Cognitive Stage, the Associative Stage, and the Autonomous Stage. The Cognitive Stage involves understanding "what to do," and requires a lot of mental effort and reliance on working memory. The Associative Stage focuses on "how to perform the task," with fewer errors and less dependence on visual feedback. The Autonomous Stage reflects high proficiency, where actions require minimal cognitive effort. While this model is useful, it does not fully account for skill transfer (Gass, 1999), individual differences, or neuropsychological factors.

Masters (1992) later added neuropsychological factors, distinguishing between two types of motor learning: explicit and implicit. Explicit motor learning involves conscious hypothesis testing, leading to declarative knowledge, relying on verbal cues, and working memory. In contrast, implicit motor learning involves minimal conscious hypothesis testing, fostering procedural knowledge and functioning independently of verbal cues and working memory. Thus, according to Masters (1992) skills can be acquired through either explicit (working memory-dependent) or implicit (working memory-independent) learning processes.

1.4. Working Memory and Skill Acquisition

Miller (1956) first introduced the concept of working memory, highlighting its essential role in our ability to process and understand information, influencing our understanding of cognitive processes and how they relate to learning and performance. Later, working memory was defined as a short-term, conscious system that stores and manipulates task-specific information to achieve desired outcomes. Unlike long-term memory, working memory is more susceptible to interference (Baars, 1997; Baddeley, 2002). Working memory plays a critical role in conscious task control, allowing individuals to respond to verbal commands and adapt to varying task demands. Research shows that individuals with greater working memory capacity can store more verbal information and maintain better focus compared to those with lower capacity. They are also more capable of managing higher cognitive loads and resisting distractions (Baddeley, 2002). Furthermore, working memory functions as a task-specific, self-updating system. When a desired outcome is not achieved, it can discard ineffective strategies or refine responses after multiple attempts, thereby promoting skill enhancement and continuous learning.

Miller (1956) explored the holding capacity of working memory, suggesting that it can retain "seven plus or minus two" items at a time. More recent research, however, indicates that the average capacity of a person to hold information in working memory may be four to five items only (Gilchrist et al., 2008). Diamond (1985), a leading researcher in infant psychology, explored task retention time in conscious memory. He deduced that infants at 7 months can only retain information for just 2 seconds, while this period extends to 10 seconds by 12 months, illustrating cognitive development across maturation stages. Building on Diamond's (1985) findings, Brockmole and Logie (2013) showed that working memory capacity peaks in early childhood and

gradually declines with age, forming a bell-shaped curve. Their research also indicated that visual memory tends to fade more quickly than verbal memory as people age.

In conclusion, Miller's (1956) introduction of working memory has fundamentally transformed the understanding of cognitive processes and their implications for learning and performance. Working memory serves as a critical system for temporarily storing and manipulating information, essential for task engagement and skill acquisition. Its inherent capacity limitations underscore the challenges individuals face in retaining and processing information effectively. Additionally, research highlights that those with greater working memory capacity are better equipped to manage cognitive demands and maintain focus. Ultimately, working memory plays a vital role in enabling continuous improvement, allowing learners to refine skills and enhance overall performance. Overall, there is a little doubt that working memory plays an essential role in skill acquisition and task-specific information processing.

1.4.1. Working Memory's contribution to Skill Learning

Baddeley and Hitch (1974) argued that Working Memory relies on a "central executive" that is responsible for managing the incoming information (input) and cognitive functions along with providing a refined output while directing attention. It has two underlying primary sub systems or "slave systems," the *visuospatial sketchpad* and the *phonological loop.* The *visual sketchpad* regulates all the visual and the spatial commands whereas *the phonological loop* controls all the auditory input. Baddeley (2000) expanded his theory by adding another component to his model, an "episodic buffer," which was suggested to form a link between the short-term memory and the long-term memory and was believed to be controlled consciously. Later the role of the episodic buffer was redefined as a crucial integration between short-term memory, long-term memory, and

other systems (Baddeley, 2012) as displayed in Figure 1. Despite the significance of his contribution Baddley's work faced a lot of criticism, especially regarding the nature and role of the central executive. Baddeley's contributions to working memory are intricately linked to skill acquisition in several key ways. His multi-component model emphasizes how distinct types of information, such as verbal and visual-spatial data, are processed simultaneously, which is essential in many skill learning contexts. The central executive plays a crucial role in managing attention and resources, allowing learners to focus on relevant information and adapt to changing conditions.

Additionally, Baddeley's insights into cognitive load highlight the importance of minimizing overload to enhance learning efficiency. This understanding enables educators and trainers to design strategies that break tasks into manageable parts, facilitating better skill acquisition. Overall, his work underscores the dynamic nature of working memory in supporting real-time adaptation and continuous improvement during the learning process. Regardless, his theory provides the best explanation of how cognitive and conscious control are highly integrated in skill acquisition. Baddeley's model is versatile and well-supported by research, making it a strong candidate for understanding and enhancing skill learning across various domains.

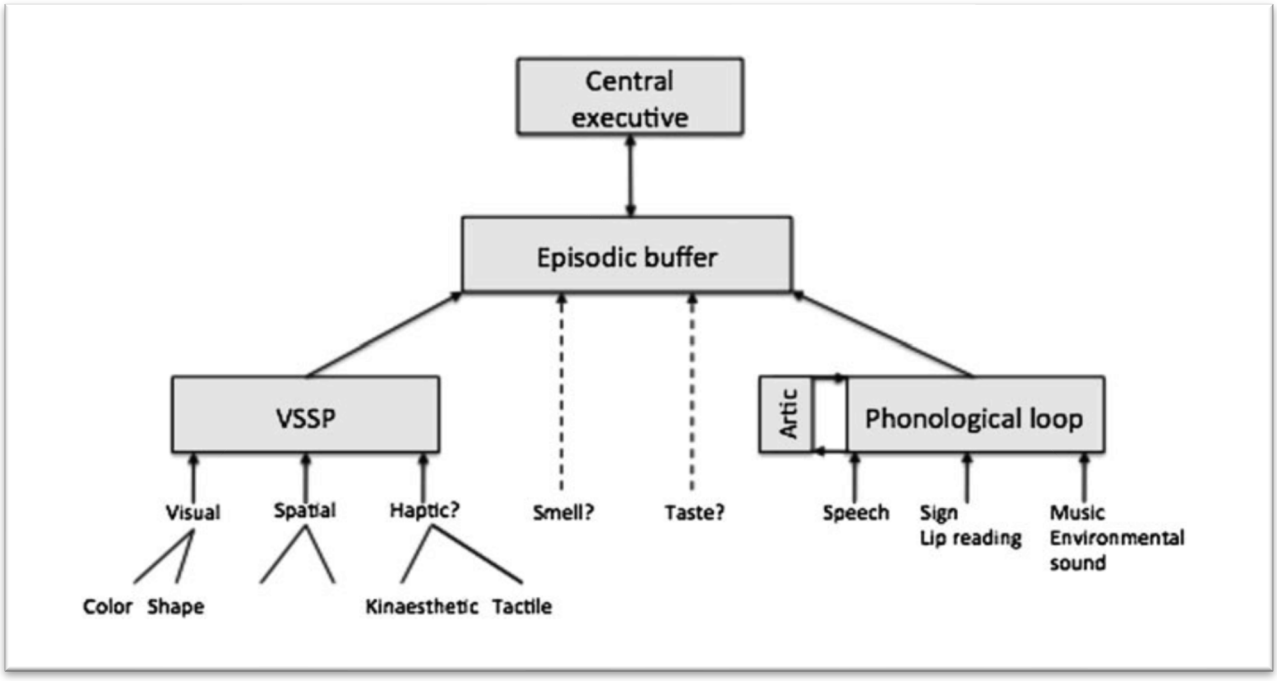

Figure 1: Baddeley's Working Memory Model (Baddeley, 2012, p:23)

1.5. Implicit v/s Explicit Learning

Implicit and explicit learning differ in several ways. Explicit learning occurs with conscious awareness and intentional effort, while implicit learning happens without awareness, often through experience or exposure. Explicit learning involves deliberate processing, whereas implicit learning relies on automatic processes driven by repetition. Engaging in a task with conscious awareness or cognitive control can sometimes diminish performance effectiveness or even impede the ability to complete the task. It happens because cognitive load can slow down response times and hinder control and coordination, this phenomenon is referred to as the "Memory Drum" theory. (Henry & Rogers, 1960). Building on this idea, Masters (1992) proposed that as individuals become more experienced with a task, they need less cognitive effort and awareness of its procedures. This

suggests that more experienced individuals often rely on implicit strategies rather than explicit strategies.

Research by Manginelli et al. (2013) found that simultaneous tasks that engage working memory do not significantly impact implicit learning, showing no positive or negative effects. This suggests that implicit learning is robust and remains unaffected even under cognitive load, highlighting its resilience in various conditions (Capio et al., 2013).

Furthermore, research by Yang et al. (2020) revealed that implicit memory is more potent and feasible, remaining unaffected by various learner characteristics such as task complexity, age, or mental load during performance. This notion is supported by a study conducted by Verburgh et al. (2016) on soccer players. Their findings showed that players relying on implicit strategies outperformed those using explicit strategies, even under the same cognitive load. Additionally, the implicit group took longer to acquire the skill, highlighting the trade-off between how quickly they learned and how well they performed.

Fitts and Posner (1967) suggested that when a task is acquired through cognitive learning, the knowledge is rule-based, and as it transitions into autonomous learning, those rules diminish and become less conscious. However, this perspective was challenged by Jiménez and Méndez (2001), who argued that the knowledge gained during implicit motor learning is neither dependent nor related to explicit learning. They contended that both types of learning have distinct protocols and processes. Moreover, implicit learning requires minimal cognitive support compared to explicit learning. This distinction emphasizes the unique traits of implicit learning, enabling smoother skill acquisition without the need to consciously apply rules.

In addition to the limited capacity of working memory, implicit memory is often regarded as permanent and long-lasting, remaining unaffected by sedentary degradation (Reber & Kotovsky, 1997; Vaidya et al., 2007). Vaidya et al. (2007) also described implicit memory as ontogenetic in nature, meaning it evolves over generations, like the phylogenetic traits that enable humans to walk. This type of memory is acquired with minimal conscious effort, allowing tasks to be performed unconsciously and fluently.

This characteristic is particularly evident in work done by Masters (1992) which demonstrated that complex movements can be learned implicitly without explicit knowledge, with participants in the implicit learning group showing stable performance under pressure. He proposed that movements can be acquired or improved implicitly, demonstrating that complex movements can be learned without explicit knowledge. In his study, one group practiced the golf putting task with explicit instructions, while a second group practiced without instructions and engaged in a concurrent random letter generation task to suppress working memory (implicit motor learning). A third group learnt through discovery, without instructions or secondary tasks. All groups showed improvement over 400 trials, but the implicit motor learning group had a slower learning rate. After training, they reported the least verbal knowledge and displayed performance that remained stable under psychological pressure, unlike the explicit and discovery learning groups.

These results indicate that verbal declarative knowledge is not essential for motor learning and may impair performance under pressure. The stability of performance in the implicit learning group highlights the effectiveness of developing implicit memory during skill acquisition. Implicit memory is characterized by its permanence and resilience, often unaffected by the degradation associated with sedentary behavior. Research indicates that implicit memory evolves over generations, reflecting an ontogenetic nature akin to the phylogenetic traits that enable humans to

walk. This type of memory is acquired with minimal conscious effort, allowing individuals to perform tasks unconsciously and fluently. Together, these insights emphasize the critical role of implicit memory in enhancing learning and performance across various contexts.

1.5.1. Implicit Learning Protocols

A variety of methods have been used to cause implicit motor learning. Dual-task learning, which involves executing a secondary cognitive task alongside a primary motor task, reduces conscious movement processing and fosters non-conscious motor learning (Masters, 1992; Maxwell et al.; 2000). Performing a cognitive secondary task during movement learning has shown limitations, primarily slowing the learning rate. For instance, Maxwell et al. (2000), found that participants engaged in a secondary task during 3,000 golf putting trials learned more slowly than those who learned through discovery, although their performance was similar in a delayed retention test without the secondary task. Enforcing secondary tasks can also be challenging, as participants often struggle to process both tasks simultaneously, leading to serial processing, particularly when mentally fatigued. This can temporarily engage the primary task since working memory may not be fully occupied. Additionally, applying the secondary task paradigm in practical settings is difficult, as coaches may find it hard to ensure that all team members consistently perform the secondary task during practice. While some studies question its effectiveness (Gucciardi & Dimmock, 2008), others suggest that dual-task practice can enhance learning outcomes (Goh et al., 2012).

Analogy learning is also used to cause implicit motor learning. During analogy learning, a metaphor is presented to simplify the explicit information that is used to promote understanding of the movements. Liao and Masters (2001) first tested this approach. Instead of giving detailed

technical explanations about the mechanics of hitting a forehand topspin shot in table tennis, they suggested that an instructor might use a metaphor that simplifies the task, making it easier for novices to understand and execute the movement intuitively. This method aligns with the principles of implicit learning, as it helps learners acquire skills without relying heavily on explicit rules or conscious thought. The study illustrates how this approach can lead to effective performance while minimizing cognitive load, especially under stress or distraction. Also, in a study by Lam, Maxwell, and Masters (2009), analogy learning was used in basketball shooting, with participants told to "finish the shot like reaching into a cookie jar" instead of concentrating on specific shoulder or arm movements. This method resulted in modest performance enhancements, indicating effective implicit skill acquisition.

Another approach is errorless learning, which minimizes errors by structuring the environment to reduce the difficulty of the taskBy doing this, it is thought that learners are less likely to test hypotheses about how to correct errors during practice. Maxwell et al. (2001) investigated how the number of errors made during the learning of golf putting affected the adoption of explicit versus implicit learning modes of learning. It was found that errorful learners tended to use explicit, hypothesis-testing strategies during practice, which resulted in a build-up of verbalizable rules and knowledge that caused performance declines under dual-task conditions. Conversely, errorless learners maintained robust performance even when faced with additional tasks. By reducing errors, learners engaged less in explicit processing, favoring implicit learning processes that enhance skill acquisition and resilience to distractions. Overall, the findings suggest that minimizing errors promotes a more intuitive and stable approach to learning motor skills.

Each method for inducing implicit learning has its strengths and limitations, and their effectiveness largely depends on the task specifics and individual responses. Tailoring the learning method to the task and the learner's unique characteristics is essential for optimizing outcomes.

1.6. The neural roots of motor control

Research has consistently supported the notion that learning new skills can lead to structural plasticity in the brain. One of the earliest studies Konorski (1948) suggested that learning induces morphological alterations in neural networks. This foundational work paved the way for numerous subsequent studies that have demonstrated how skill acquisition can result in changes to the brain's structure, enhancing our understanding of the dynamic relationship between learning and brain adaptation.

In another notable study, Nudo et al. (1996) discovered reorganization in the digital motor cortex of post-stroke patients following motor activity in food retrieval training. These findings underscore the brain's capacity for adaptation in response to learning experiences. Identical results were demonstrated by Sagi et al. (2012) in a computer-based task, revealing structural plasticity in the hippocampus and prefrontal regions due to active engagement in short-term memory tasks.

Boyd and Winstein (2004) conducted a study to investigate the effects of cerebellar dysfunction on motor task learning using a simple repeated key-pressing task. They divided participants into two groups: one consisting of individuals with normal brain function (the brain-fit group) and the other composed of individuals with cerebellar injuries (the brain-injury group). The study found that those with cerebellar dysfunction had significantly impaired learning of the task, which was evidenced by slower response times and lower accuracy compared to the brain-fit group. This suggests that the cerebellum plays a crucial role in facilitating efficient motor learning and

performance, highlighting how neurological impairments can affect skill acquisition and execution. Furthermore, the study highlights the distinction between explicit and implicit learning. Explicit learning is largely governed by the medial temporal lobe, which is essential for memory formation and recall. In contrast, implicit learning engages various dispersed neural regions and does not rely as heavily on conscious recall. This explains why damage to a single brain region may not completely impair implicit learning processes. The cerebellum is vital for implicit task learning, underscoring its importance in motor skill development.

Research by Poldrack et al. (2001) further elucidated the neural dynamics underlying implicit and explicit memory. They found that implicit memory is characterized by hyperactivity and increased connectivity in the striatum, while the medial temporal lobe is less active; conversely, explicit memory relies on the medial temporal lobe and shows decreased striatal activity. This difference highlights the distinct neural mechanisms that govern implicit and explicit memory systems.

Moreover, numerous studies have shown that repeated practice of motor tasks over extended periods leads to lasting changes in both brain structure and task performance due to retention (Dayan & Cohen, 2011; Landi et al., 2011). Various stages of task execution require the involvement of various brain regions, indicating that implicit and explicit learning depends on different neural mechanisms. With every skill acquired, the brain adapts both structurally and functionally, reflecting its remarkable capacity for neuroplasticity.

1.7. Neuroplasticity: The spine of adaptive skill performance

Neuroplasticity, derived from “neuro” (nervous system) and “plastos” (to adapt), refers to the brain’s ability to change and repair itself. It includes short-term adjustments and long-term

structural changes in synaptic connections among neurons in response to strong or persistent stimuli, reflecting the brain's capacity to adapt to new experiences (Cramer et al., 2011).

Brain plasticity, according to the Plasticity Hypothesis, involves gradual changes in neural connectivity, either through physiological connections or anatomical reorganization, in response to external or internal stimuli (James, 1890). Research by Winstein and colleagues (2015) has demonstrated that neuroplasticity is essential for learning, relearning, adapting, compensating, rehabilitating, and recovering various skills across the lifespan, from childhood to old age and even following illness (Weinstein et al., 2015). Neuroplasticity is highly influenced by developmental stages and motor learning processes (Chang, 2014; May, 2011). Dancause et al. (2005) indicated that neuroplasticity varies across developmental stages. It significantly declines from the developmental stage to the age stage but increases again following brain injury and during rehabilitation protocols. A discernible pattern emerges (Supplementary Motor Area is activated during the recovery of functional activity) can lead to significant improvements in motor skills and brain plasticity (Murphy & Corbett, 2009; Pekna et al., 2012). These findings highlight the brain's remarkable adaptability in response to learning, development, and injury.

The belief that brain plasticity was limited to early developmental stages and that cognitive decline with aging marked the end of significant brain plasticity (Voss et al., 2017) was challenged by Ramscar et al. (2014), suggesting that cognitive decline in older adults might be due to the increased neural load required to process and integrate new information with existing memories, as both experience and knowledge expand over time. Also, it was explored that several types of learning engage distinct brain regions: implicit learning primarily involves the cerebellum and basal ganglia, while explicit learning is mainly controlled by the prefrontal cortex (Meehan et al., 2011). As individuals age, there is a noticeable shift in brain activity, with motor functions

increasingly relying on the prefrontal and parietal cortices rather than deeper structures. This suggests that as primary motor areas decline, the brain compensates by engaging outer areas, leading to increased cognitive load from greater reliance on planning and sensory integration.

Significant research has focused on identifying the specific neural circuits involved in motor learning. Hikosaka et al. (2002) highlight the formation of new neural circuits in the Cortico-Cerebellar (CC) and Cortico-Striatal (CS) areas during motor skill learning; where Motor Area 1 (M1) is essential for skill acquisition (Rioult-Pedotti et al., 2000). Ungerleider et al. (2002) proposed that skill learning results from interactions between various brain regions. Their theory suggests communication between the Cortico-Striatal (CS) and Cortico-Cerebellar (CC) areas during the learning of new skills, and between the parietal cortex, putamen, Supplementary Motor Area (SMA), and globus pallidus during the performance of established tasks. Additionally, the cerebellum is activated during the acquisition and refinement of new skills.

Further research by Doyon et al., (2005) investigated the stages of motor learning and their corresponding neural substrates, proposing a five-stage model for skill acquisition. Initially, skills are learned rapidly (significant improvement after the first attempt, but the learning rate slows down with practice). This is followed by a consolidation stage, where task performance improves after a latency period of at least six hours, leading to the automatic phase of skill learning, characterized by reduced cognitive demands and more seamless performance. The final stage is retention, which ensures that the skill is stored as a memory and can be executed automatically without further practice, even after extended periods. This model highlights the dynamic nature of skill acquisition and the importance of various stages for achieving long-term mastery (Doyon & Benali, 2005). In the initial stages of skill learning, both the Cortico-Striatal (CS) and Cortico-Cerebellar (CC) areas are involved. However, as skills become automated and retained, activity

shifts to the CC region. This shift reflects changes in brain activity from the novice stage to the retention phase of skill learning (Doyon & Benali, 2005; Doyon et al., 2003).

1.7.1. Etiology of Neuroplasticity

While William James (1890) was the first to introduce the concept of plasticity, it gained prominence through the work of Donald Hebb in 1949. Hebb's theory offers a framework for understanding synaptic plasticity, proposing that synaptic connections can be created or strengthened through repeated activation, even in the absence of direct connections between an axon and a dendrite.

Hebb (1949) explained that when neurons are in proximity and repeatedly fire together or individually, metabolic changes occur. This firing can lead to new bond formation between neurons, reinforcing connections. Hebb famously summarized this with "cells that fire together, wire together," emphasizing that repeated co-activation strengthens or creates synapses. This concept is foundational in understanding how learning and memory are represented in the brain.

Kolb and Gibb (2011) described that the brain reorganizes in response to stimuli, with plasticity classified into three types. Experience-Independent Plasticity occurs during prenatal development and is driven by genetic factors. Experience-Expectant Plasticity occurs in response to environmental inputs, such as sensory experiences, and is essential for proper connections, like those of retinal ganglion cells during critical periods. Experience-Dependent Plasticity, involves neuronal changes from unique individual experiences, including learning and injury recovery. These categories show how the brain adapts based on genetic programming and environmental influences (Hebb, 2005).

Research by Squire et al. (2012), examined mechanisms of plasticity, including Denervation Super-sensitivity, Long-Term Potentiation (LTP), and Long-Term Depression (LTD). Denervation Super-sensitivity occurs when neurons become more responsive to neurotransmitters after losing input from others. LTP is a lasting increase in synaptic strength due to repeated stimulation, crucial for learning and memory. In contrast, LTD is a prolonged decrease in synaptic strength that helps fine-tune neural circuits and eliminate redundant connections. Together, these mechanisms illustrate how the brain adapts and reorganizes in response to experiences and environmental changes.

1.7.2. Stratification of Neuroplasticity: Fundamental and Cytological

Brain plasticity can be classified into Developmental Plasticity, Myelin Plasticity, Adult Plasticity, and Adaptive vs. Maladaptive Plasticity. Developmental Plasticity, as described by Innocenti et al. (1985) and Huang et al. (1999), occurs during critical developmental periods known as "sensitive" or "critical periods." This form of plasticity is essential for normal brain development and function.

Myelin Plasticity refers to changes in myelination that affect neural signal conduction, impacting cognitive functions during development and aging. These changes influence tasks like signal amplification and computation and depend on factors such as axon diameter and length, which are crucial for efficient neural communication. This concept underscores the brain's ability to adapt and reorganize throughout life (Huang et al., 1999; Innocenti et al., 1985; Innocenti, 1995; Innocenti et al., 2016).

Adult Plasticity challenges the notion that the adult brain lacks plasticity, demonstrating slow myelination of neurons that indicates ongoing plastic changes (Lucassen et al., 2020). This concept of brain adaptability is further refined by Oberman and Pascual-Leone (2013) who described

adaptive plasticity as the brain's capacity to adjust according to environmental factors, pathologies, or diseases. In contrast, Ayoub and Rakic (2015) explored the concept of maladaptive plasticity, which occurs when developmental processes are disrupted or in response to injury or disease.

Based on long-term depression (LTD) and long-term potentiation (LTP), plasticity can be divided into "Hebbian Plasticity," which refers to long-term potentiation caused by twitching or spasmodic stimulation (Collingridge & Bliss, 1987, 1995). This type of plasticity can typically be categorized into two types: classical and non-classical {latter exemplified by Purkinje fiber connections in the cerebellum, as discovered by Ito (2002)}, or the structural plasticity, as described by Geinisman et al. (2001), refers to the activation of silent, unidentified synapses that are present in the nervous system. When these synapses are excited or new synapses are formed, it is termed structural plasticity. This category also includes neurogenesis, which occurs in regions such as the hippocampus, olfactory areas, and the amygdala (Gould et al., 1999).

Evidence of meta-plasticity was observed in the visual cortex by Bienenstock et al. (1982), following the BCM[2] rule, which suggests that plasticity occurs in relation to the frequency and history of stimulation. Homeostatic plasticity maintains the stability of neural networks by balancing excitatory and inhibitory inputs. This process ensures that overall neural activity remains within an optimal range, allowing the brain to adapt to changes in input while preventing overexcitement or excessive inhibition. By adjusting the strength of synaptic connections, homeostatic plasticity plays a crucial role in preserving the integrity and function of neural circuits. (Wexler & Stanton, 1993).

[2] BCM theory (Bienenstock, Cooper, and Munro 1982) refers to synaptic modification theory proposed by Elie Bienenstock, Leon Cooper, and Paul Munro in 1982 for measuring the selectivity of neurons and its dependency on neuronal input in primary sensory cortex. The model states that plasticity at a given synapse is bidirectional (i.e. the level of afferent activity regulates point of crossover from LTD to LTP of active synapses).

1.8. Implicit and Explicit Neural Correlations

It is well established that learning induces plasticity in the brain, leading to structural and functional changes in response to experience. Numerous studies have been published that investigate alterations in specific brain areas during several types of motor learning. For instance, research by Doyon et al. (2002) demonstrated that as a task becomes more automated and implicit, neural recruitment shifts from the cerebellar nuclei to the dentate nucleus. This shift reflects the transition from controlled processing, which requires conscious effort, to automatic processing, which occurs without conscious awareness.

Similarly, Schendan et al. (2003) observed neural activity in the medial temporal lobe during a Serial Reaction Time Task (SRTT), even when participants were unaware of the sequence, they were learning highlighting the capacity for implicit learning to take place without any conscious recognition.

Shibasaki et al. (1993) found evidence of co-activation in fronto-parietal areas, particularly the prefrontal cortex and posterior parietal cortex, during explicit learning tasks, which are essential for conscious information processing. In the preliminary stages of implicit motor learning, activation of the contralateral primary sensorimotor cortex (SM1) was noted. Later, increased activation was observed in the ipsilateral SM1 and supplementary motor area (SMA). The involvement of the ipsilateral SM1 is supported by findings from Shibasaki et al. (1993) and Chen et al. (1997) which indicate that this region is the control center for sequential learning, thus promoting implicit acquisition.

Several studies have also focused on inducing brain plasticity in humans through various medical interventions. For instance, Teo (2009) showed that neuroplasticity can be facilitated through

methods like transcranial magnetic stimulation (TMS), which modulates cortical activity via single or repeated sessions. Other promising techniques include paired associative stimulation (combining TMS with peripheral nerve stimulation), transcranial direct current stimulation (which uses weak electrical currents), and direct vertical stimulation. Additionally, pharmacological agents such as noradrenergic, dopaminergic, cholinergic, GABA-ergic, glutamatergic, and endocannabinoid compounds may enhance neuroplasticity.

Despite extensive research on the neural basis of implicit and explicit learning, a significant gap remains in our understanding of how these distinct types of learning impact neuroplasticity. There is no clear consensus on whether implicit or explicit learning leads to greater or more beneficial neuroplastic changes. Both types of learning engage different neural circuits and may influence brain plasticity in unique ways, but further studies are needed to directly compare their neuroplastic effects. This gap forms the basis for current research hypotheses, which aim to elucidate whether implicit or explicit learning promotes better neuroplasticity and under what conditions this occurs. Understanding these dynamics could have important implications for enhancing learning and developing effective rehabilitation strategies, leading to more targeted interventions in clinical settings.

To evaluate adult plasticity, behavioral assessments are used, such as skill acquisition tests and cognitive evaluations, to measure improvements after training. Neuroimaging techniques like fMRI and diffusion tensor imaging (DTI) observe changes in brain activity and white matter integrity. Electrophysiological methods, such as EEG and TMS, assess brain wave patterns and excitability before and after training.

For Hebbian plasticity, neurophysiological recordings, including long-term potentiation (LTP) and long-term depression (LTD) experiments, directly measure synaptic strength changes in response

to specific stimulation protocols. Cellular techniques, such as patch-clamp electrophysiology and immunohistochemistry, analyze synaptic responses and protein expression related to synaptic changes. Behavioral tasks that engage Hebbian mechanisms also provide insights into learning-related plasticity. Given this focus, the study will primarily relate to adult plasticity.

This study aims to investigate the differences in neuroplastic changes resulting from implicit versus explicit learning of a traditional Dutch shuffleboard game (Sjoelbak). Building on the existing research gap regarding how these distinct learning types impact neuroplasticity, we employed baseline electroencephalography (EEG) to measure changes in brain activity before and after practice. By assessing neuroplasticity in the context of Sjoelbak, this research seeks to clarify whether implicit or explicit learning leads to more significant neuroplastic changes. Understanding these effects could provide valuable insights for enhancing learning strategies and developing targeted rehabilitation interventions, aligning with the broader goal of elucidating the dynamics of adult plasticity.

Chapter 2: Measuring Brain's malleability: Plasticity

Neuroplasticity can be measured using various methods - electromyography (EMG) assesses muscle activity, electroencephalography (EEG) captures brain electrical activity, and magnetic resonance imaging (MRI) provides structural brain images. Functional MRI (fMRI) allows real-time observation of brain activity by detecting blood flow changes, while transcranial magnetic stimulation (TMS) can assess and induce brain activity changes. These tools offer valuable insights into how the brain adapts and reorganizes itself.

2.1. Electroencephalography

Electroencephalography (EEG) is valuable for studying changes in brain activity that are associated with neuroplasticity. The stratum corneum of the scalp has high electrical impedance, making it suitable for recording electrical discharges generated by the brain. EEG captures the brain's oscillatory activity, offering insights into behavioral and cognitive states. While EEG has limitations, such as poor spatial resolution and difficulty in pinpointing specific brain areas, it remains a useful, non-invasive method for studying neuroplasticity, as changes in brain wave patterns reflect adaptation following injury or learning.

2.1.1. Alpha, beta, theta, and gamma waves in EEG studies

Among the various EEG waveforms, delta waves (0.5-4 Hz), theta waves (4-8 Hz), alpha waves (8-13 Hz), and beta waves (13 Hz and above) are considered the most significant (van Wijk et al., 2012). Delta waves are the slowest brain waves and are typically associated with restorative processes and deep sleep. Theta waves are linked to light sleep, relaxation, and memory processes,

reflecting cognitive functions. Alpha waves are linked to meditative states and indicate the brain's efforts to regain stability, with increased activity suggesting a return to equilibrium after workout. In contrast, beta waves are associated with active thinking, problem-solving, and motor control, Dyck and Klaes (2024) observed a marked suppression of beta power during initial stages of strategy-based learning. Also Korka et al. (2023) displayed a notable decrease in post-movement beta rebound (PMBR) when task performance was conditioned for strategic re-aiming using a cognitive strategy, compared to the implicit approach relying on visual cues. Related results were revealed by Jahani et al. (2020) where beta power was attenuated when participants explicitly re-aimed to improve task performance through cognitive control. Research indicates that beta power modulation is crucial during motor sequence learning tasks. Increased beta event-related desynchronization (ERD[3]) is observed during implicit learning conditions, suggesting that beta waves serve as biomarkers for this type of learning. Studies, such as those by Pollok et al. (2014) have shown a direct correlation between beta ERD and behavioral performance. This relationship underscores the role of beta oscillations in facilitating learning and memory processes during motor tasks (Dyck & Klaes, 2024).

The alpha rhythm, the most dominant EEG rhythm, is associated with a relaxed yet alert state. It can be influenced by cognitive tasks; for example, engagement during sensorimotor activities increases alpha activity through event-related synchronization (ERS) Conversely, active engagement decreases alpha waves, a phenomenon called event-related desynchronization (ERD). Greater ERD indicates higher activation in specific brain regions, with both alpha and beta rhythms decreasing as neural synchronization increases (Pfurtscheller & Lopes da Silva, 1999). A greater ERD refers to higher activation of brain region where alpha and beta rhythms demonstrate a

[3] the event-related decrease in the brain wave

decrement with increase in neural synchronization. As per Klimesch (1999) and Scerbo et al. (2003) increased task difficulty or cognitive load tends to decrease alpha activity while simultaneously increasing theta wave activity. This shift reflects a transition from a relaxed state to one requiring greater cognitive effort.

These findings suggest that EEG rhythms actively represent the brain's response to motor activity, injury, and rehabilitation, rather than being mere passive indicators. Also, beta waves are integral indicators of neuroplasticity, facilitating cognitive control and motor learning. Their modulation reflects the brain's adaptability and engagement during various tasks, leveraging these insights allows for the development of strategies that optimize motor learning, enhancing its effectiveness.

2.1.2. Cardinal Electrode Regions for Assessing Neuroplasticity

To study neuroplastic changes, it is essential to examine specific brain regions that exhibit these alterations. For instance, Butt et al. (2020) assessed brain plasticity following stroke and the effects of rehabilitation using an Ag|AgCl EEG cap with the Compumedics Neuroscan system. Butt et al. (2020) used electrodes at FP1, FP2, FC4, C4, CP4, FC3, C3, CP3, Cz, and CPz, with reference electrode on the ipsilateral earlobe and FPz (as the ground to reduce noise). EEG signals were amplified using a Grael 4 EEG amplifier, sampling at 2048 Hz while maintaining electrode impedance below 5 kΩ. A notch filter eliminated power line noise, and a low-pass filter at 5 Hz was used to focus on movement-related cortical potentials (MRCPs) in the delta band (0.5-5 Hz). Independent Component Analysis (ICA) removed eye-related artifacts by excluding components exceeding 100 μVpp from FP1 and FP2. This approach enabled a more accurate assessment of brain activity related to neuroplasticity and rehabilitation, offering insights into the brain's adaptation following injury and the effectiveness of therapeutic interventions.

The research conducted by Giaquinto et al. (1994) demonstrated a positive correlation between increased alpha wave activity and improvements in the Barthel Scale, a tool used to assess activities of daily living (ADLs) and recovery from disability following brain injury. This study also noted a similar trend where a decrease in delta wave activity corresponded with better performance on the Barthel Scale. In this study, EEG electrodes were strategically placed at locations F3-C3, F4-C4, C3-T3, C4-T4, T3-T5, T4-T6, T5-O1, and T6-O2. The EEG signals were filtered within a frequency band of 0.2 to 32 Hz, and the electrode impedance was maintained below 3 kΩ to ensure reliable data collection. The findings suggest that changes in brain wave patterns, particularly the modulation of alpha and delta waves, may be indicative of neuroplasticity representing recovery progress as well enhanced performance in individuals.

A more precise experimental setup was designed by Romero et al. (2008) to examine cognition-related EEG changes through Event-Related Synchronization (ERS) and Event-Related Desynchronization (ERD). The study used a 17-electrode EEG setup with electrodes placed at FT0, F3, F4, F7, F8, C3, C4, P3, P4, T3, T4, T5, T6, O1, O2, Fz, Cz, and Pz, along with mastoid and left forearm electrodes for grounding. Two bipolar channels recorded vertical and horizontal eye movements. EEG signals were collected for about 2000 ms, including a 1000 ms pre-stimulus period, amplified 2000 times, filtered between 0.1 and 300 Hz, and digitized at 1000 Hz. Recordings exceeding 50 μV were discarded to reduce noise. The findings indicated increased theta wave synchronization in the frontal and mid-scalp regions, highlighting the involvement of the frontal lobe and hippocampus in semantic motor retrieval and memory encoding. A significant rise in beta event-related desynchronization (ERD) over the central scalp reflected increased neural activation during cognitively demanding tasks. Event-related potentials (ERPs) at 300 ms were linked to control processing, while those at 500 ms indicated memory recognition. The study

emphasized the importance of ERP analysis in skill acquisition, showing a shift in ERPs from fronto-central to Centro-parietal regions as learning progressed, providing valuable insights into the neural dynamics of learning.

Gong et al. (2020) explored neuroplasticity and Sensory Motor Rhythm (SMR), specifically in the frequency range of 12-15 Hz, using an extensive 32-electrode arrangement. Electrodes were strategically placed at various locations, including Pp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, Fz, Cz, Pz, FC3, FC4, CP3, FT7, FT8, TP7, TP8, FCz, CPz, Oz, PO3, and PO4. Electrode impedance was kept below 5 kΩ, with ground electrodes on the forehead and reference electrodes over the mastoids. Data was collected in two 5-minute sessions; one with eyes open and one with eyes closed. Analysis was conducted using MATLAB 2014 and EEGLAB software, employing Independent Component Analysis (ICA) to remove eye movement artifacts from Fp1 and Fp2, excluding data with coefficients of 0.8 or above. The findings revealed a direct correlation between higher sensory motor rhythm (SMR) and increased attention and awareness during tasks, suggesting that enhanced SMR may facilitate cognitive engagement and focus, underscoring the potential of neuroplasticity in improving attention-related tasks.

2.1.3. EEG interpreting the brain connectivity and task power in Skill Acquisition

Amo et al. (2017) emphasized the significance of Cz in detecting skill learning. It was revealed that as learning progressed, gamma waves increased, and the plasticity index (IP), defined as the final state of gamma waves divided by the initial state, was positive. Along with it, the significance of Task Related Power was highlighted in research conducted by Bootsma et al. (2021). The findings showed that lower alpha and beta power during training (relative to baseline) were associated with greater brain activity. Notably, alpha power returns to normal after 24 hours, while

beta waves return to normal after 2-3hrs of inactivity and both are deemed crucial for measuring behavioral transfer which is a way to measure neuroplasticity. Parietal alpha and motor beta activity were considered as key indicators of plasticity in the study. After task improvements in response time were noted in younger adults, while older participants showed enhanced task accuracy. Furthermore, a decrease in beta power was recorded during baseline beta power in higher task difficulty, while a decline in beta power from baseline to after practice and its return to baseline after 24 hours represented higher consolidation primarily in motor areas.

Pascual-Leone et al. (2005) made significant contributions to our understanding of neuroplasticity with their research on motor learning and skill acquisition. Their work highlighted how the brain undergoes structural and functional changes in response to learning new skills. Specifically, they demonstrated that learning induces plasticity, characterized by changes in cortical and subcortical regions. This includes processes such as dendritic arborization (the growth of dendritic branches) and elongation of axonal terminals, which help create new neural connections. This foundational research set the stage for further studies into how learning affects brain connectivity

Research by Titone et al. (2022) and Rojas et al. (2018) has explored similar themes in the context of motor learning and its effects on resting state functional connectivity. Titone et al. found that motor learning significantly influences this connectivity. Specifically, they observed a decrease in beta connectivity within the somato-motor cortex, putamen, and cerebellum, referred to as the distant seeds, during the baseline or pre-task phase, indicating enhanced learning potential.

During the initial learning phase, similar effects were observed in motor areas, including the primary motor and pre-supplementary motor areas. However, in the post-task phase, beta connectivity increased. Gamma connectivity showed an initial burst in the primary motor area and parietal regions, but as learning progressed, connectivity decreased within the motor network and

between motor, ventral, and language networks. In visuomotor learning, a decline in gamma-theta connectivity was noted in the parietal region. Overall, baseline levels of beta, theta, and delta activity were negatively correlated with performance. Specifically, spikes in delta and theta activity were linked to poor initial motor learning, while elevated beta waves indicated ineffective consolidation. Additionally, beta desynchronization in the pre-task phase suggested an inverse relationship with training outcomes. These findings highlight that the connectivity of various frequency bands (i.e., beta, gamma, delta, and theta) within motor and associated networks is closely related to skill learning and consolidation.

Rojas et al. (2018) investigated the interrelationship between different brain regions during skill learning, identifying specific brain areas as "seeds." The study analyzed correlations between distinct brain networks (seeds) using the Sørensen-Dice index, which assesses similarity between sampling areas. Key networks included the Somato-Motor Functional Network (MOT) with electrodes Cz, C3, and C4; the Ventral Attention Network (VAN) with F8, T5, T6, and C4; the Dorsal Attention Network (DAN) covering C3, C4, T5, T6, and Pz; and the Language Network involving F3 and Pz. Results showed that within the MOT, connectivity was highest at Cz, followed by C3 and C4, indicating a lateralized network. In contrast, the VAN exhibited the highest connectivity at F8, followed by T5, T6, and C4. The DAN demonstrated decreasing connectivity from C3, C4, T5, and T6 to Pz and was not lateralized. Additionally, the Visual Function Network showed an increasing correlation index from Oz to O2, with O1 having the highest coefficient and exhibiting right lateralization.

Additionally, Sugata et al. (2020) explored whether resting-state functional connectivity (rs-FC) can predict motor learning performance. The study examined the relationship between beta-band rs-FC in the brain and motor learning ability. Participants first completed a random button-press

task to establish baseline motor function and neural activity, followed by a sequential motor learning task where they learned and performed a specific sequence of button presses to assess their skill acquisition.

A five-minute resting-state magnetoencephalography (MEG)[4] dataset was collected between these tasks, with data resampled to 1000 Hz and subjected to an offline band-pass filter between 0.1 and 100 Hz, along with a band-elimination filter from 58 to 62 Hz to remove environmental noise. Support Vector Machine (SVM) analysis was employed to differentiate good learners from poor learners based on rs-FC, with good learners defined as those having a motor learning index above 23.7, comprising 26 participants, while 27 were classified as poor learners.

The focus was on beta-band rs-FC between the primary motor area (M1) and several regions, including the left superior temporal gyrus, right postcentral gyrus, right superior parietal lobule, and right opercular inferior frontal gyrus. The study found that good learners exhibited significantly stronger rs-FC in these areas compared to poor learners. This enhanced connectivity was associated with superior performance in sequential motor learning tasks, enabling accurate classification of participants into good or poor learners.

These findings suggest that increased connectivity in these brain regions correlates with greater motor learning ability. Previous research, including studies by Krause et al. (2016) and Pollok et al. (2014), has established a link between beta wave activity over the Primary Motor Cortex (M1) and motor learning processes. This connection underscores the role of beta waves in the neural mechanisms underlying the acquisition and refinement of motor skills. Additionally, studies by

[4] Magnetoencephalography (MEG) is the measurement of the magnetic field generated by the electrical activity of neurons.

Gentili et al. (2015) and Mehrkanoon et al. (2016) indicate that beta wave activity is modulated by motor learning, reflecting the brain's adaptive responses to practice and skill acquisition.

2.2. Summary and Study Background

Implicit motor learning may facilitate greater neuroplasticity than explicit motor learning. This study examines the effect of these two motor learning approaches on brain plasticity, utilizing both performance metrics and EEG analysis. In the study, participants practiced a shuffleboard game, (5 training sessions with 200 trials each) in which they used their hand to slide a wooden desk into a target area as accurately as possible. Based on an experimental design first used by Masters and Maxwell (2004), implicit learning was caused by an errorless training protocol during which the target area narrowed incrementally from a wide region to a small region across sessions (100cm, 80cm, 60cm, 40cm and 20cm.), whereas explicit learning was caused by an errorful training protocol during which the target area was randomized between sessions (60cm, 100cm, 40cm, 80cm and 20cm).

Performance was assessed during a pre-test and a posttest (200 trials each) as well as a transfer test (200 trials), as transfer test serves as a valuable indicator of behavioral change, which in turn reflects underlying neuroplasticity (Amo et al., 2017; Dayan & Cohen, 2011). During the pretest and posttest participants used their hand to shuffle a wooden disc toward a target line as accurately as possible. During the transfer test, participants used a multi-curved wooden spatula to slide the disc towards the line as accurately as possible. This comprehensive design allowed assessment of both behavioral changes and neuroplastic effects resulting from implicit and explicit motor learning approaches. An OpenBCI EEG system was used to explore changes in electrical activity representative of plasticity in specific regions of the brain associated with motor learning. Data

was collected during a 60 second baseline immediately prior to the pre-test and posttest in both the errorful and errorless conditions.

Key regions of the brain that were examined in the study included (1) the premotor area that is responsible for movement selection, (2) the pre-SMA, responsible for acquiring new skills; and (3) the SMA (supplementary motor area), which coordinates movements in complex tasks requiring memory retrieval and temporal organization (Meehan et al., 2011; Sagi et al., 2012). The prefrontal cortex was analyzed for its role in behavioral changes, while the assessment of primary motor cortex enables the study of rapid reorganization of motor representations due to experience. This reorganization is believed to be a result of changes in synaptic coupling among motor cortex neurons (Sugata et al., 2020; Tamaki et al., 2013).

Beta band connectivity was analyzed as a key indicator of motor learning in the Primary Motor Cortex, an area crucial for learning (Krause et al., 2016; Pollok et al., 2014)). It is also associated with modulation following motor learning (Gentili et al., 2015; Mehrkanoon et al., 2016). Furthermore, the findings from Sugata et al. (2020) indicated that increased resting-state beta connectivity between the primary motor area (M1) and the left superior temporal gyrus correlates with superior learning performance in sequence tasks. This relationship provides a solid basis for the hypothesis in the current study. This research aims to assess brain plasticity induced by two different learning approaches: implicit and explicit. We predicted that the errorless learning protocol (implicit) would enhance resting-state functional connectivity (rsFC) in the beta band among the Cz, C3, and C4 regions of the Primary Motor Cortex and the T7 and F7 areas of the left superior temporal gyrus. Specifically, we expected positive correlations in connectivity between Cz-T7, Cz-F7, C3-T7, C3-F7, C4-T7, and C4-F7, as errorless learning demands less cognitive support than errorful learning. This expectation aligns with Sugata et al. (2020), which suggests

that stronger connectivity reflects improved learning. Although research has examined various learning protocols and their effectiveness, there is currently no study focusing specifically on the impact of implicit versus explicit learning on neuroplasticity. Our study aims to fill this gap by investigating how these two types of motor learning influence resting-state beta-band connectivity and determining which promotes greater plasticity.

Chapter 3: Methodology

3.1. Participants

Twenty-four participants (13 males and 11 females, mean age = 24.5) were randomly allocated to either an error-reduced learning group or an errorful learning group based on odd-even numbering; all the even numbered participants (2-24) were allocated to the error-reduced motor learning group while all the odd numbers one (1-23) were allocated to the errorful motor learning group. All the participants were students from educational institutions in Hamilton, New Zealand.

Before the experiment commenced, the procedure was explained to the participants, and the risks were described. All the queries were addressed to ensure that the participants had a comprehensive understanding of the tasks that they were to engage in. Participation was voluntary, and the participants were given a choice to withdraw from the research at any stage. Ethical permission for the study was provided by the institutional ethics committee and informed consent was obtained before the study began.

3.2. Apparatus

The experiment took place in a motor learning laboratory. The shuffleboard was positioned on a table. Participants sat at the table and positioned their chin on a chinrest to preserve the quality of the electroencephalography signal (EEG) by keeping head at resting state. Two small circular discs were used for hand shuffling and a multi-curved spatula was used for striking the disc during the transfer task. An Open BCI system with a Cyton Daisy Biosensing Board was used to collect EEG

data during the experiment. The system supports 16 channels sampling at 125Hz with electrodes prepositioned over respective brain regions in a cap worn by the participant. It has a 16-channel bio-amplifier with a 32-bit processor and a chip KIT™ bootloader, including the daisy board (with PIC32MX250F128B microcontroller), which is highly efficient when handling large amounts of data during electroencephalography. Electrode gel was used to enhance connectivity with the scalp whenever the impedance was high.

3.3. Motor Task

The participants performed a novel shuffleboard task. Shuffleboard is a Dutch game (Sjoelen) that requires the players to slide a small wooden disc along a wooden board (length of 3.50 meters) towards a target. Participants were provided a wooden disc (radius of 2.5 cm, height 1cm) and were instructed during the pretest, posttest, and transfer test to "try and slide the disc as close to the imaginary line/ reference line as possible". Accuracy was measured as the mean absolute distance from the center of the disc to the line. During the training phase, participants were instructed to "try and slide the disc to reach the area between the two reference lines." The reference line is the lines were designated by two markers that were positioned on either side of the board during the experiment - the participants were asked to assume a line between the markers.

3.4. Procedure

3.4.1. Pretest

On Day 1, the EEG cap was placed on the participant's head. Contact between the electrodes and the scalp was enhanced by infusing the electrode gel into the pockets of the EEG headcap. The electrodes of interest for studying brain waves were finalized to be Fp1, Fp2, Fz, Cz, Pz, F3, F4,

C3, C4, T7, T8, F7, F8. The connectivity was analyzed between M1 regions (Cz, C3, and C4) and the left superior temporal gyrus (T7 and F7) i.e., Cz-T7, Cz-F7, C3-T7, C3-F7, C4-T7, and C4-F7 were recorded. Impedance was maintained below 5000 Ω. EEG electrode 16 was used as the ground electrode over the clavicle.

The participant was guided to rest the chin on the chinrest to minimize head movements while shuffling. Baseline EEG recordings were collected before the pretest, during which the participants were asked to keep their eyes closed for 30s and then open for the next 30s. After this, the pretest was performed; participants were instructed to "try and slide the disc as close to the target line as possible." The target was set at 2.30 meters from the starting position of the disc as depicted in Figure 2. The disc's final distance from the target line was recorded using a measuring tape. The pretest consisted of 20 shuffles, after which the EEG cap was removed, and the participant was provided a 5-minute rest before the training session began.

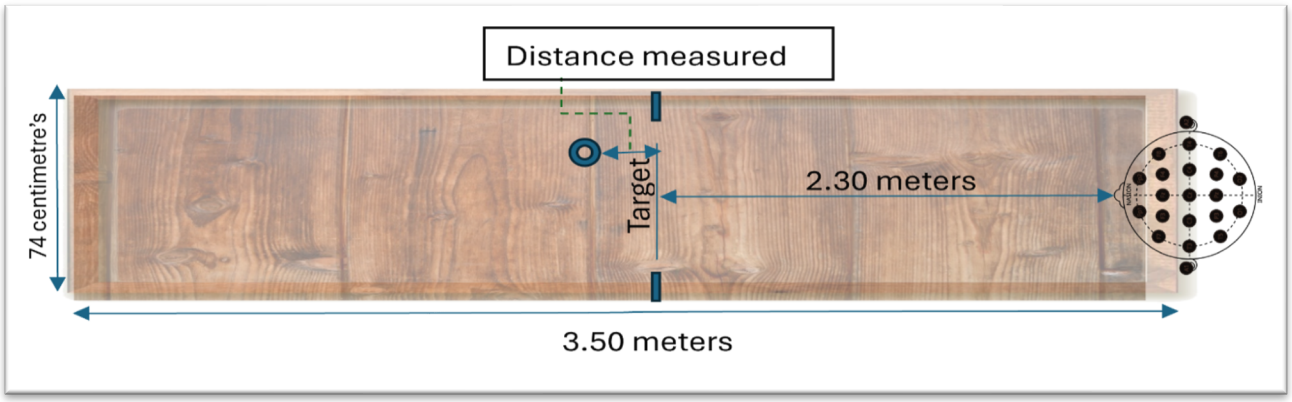

Figure 2. Layout for pretest, posttest, and transfer test for both errorless

3.4.2. Training phase

Following the pretest, participants completed a training phase consisting of five blocks of 200 trials of shuffleboard practice in either an errorless condition or an errorful condition. To create errorless learning conditions, participants were required to shuffle the disc into a target area between the two reference lines that was adjusted in increments of 20cm for each block of 200 trials from a wide margin (100cm) to a small margin (20cm). To create the errorful learning conditions, participants were required to shuffle the disc into a target area between the two reference lines that was adjusted in increments of 20cms in a random order ranging between small (20cm) and wide (100cm) in the errorful condition (see Figure 4).

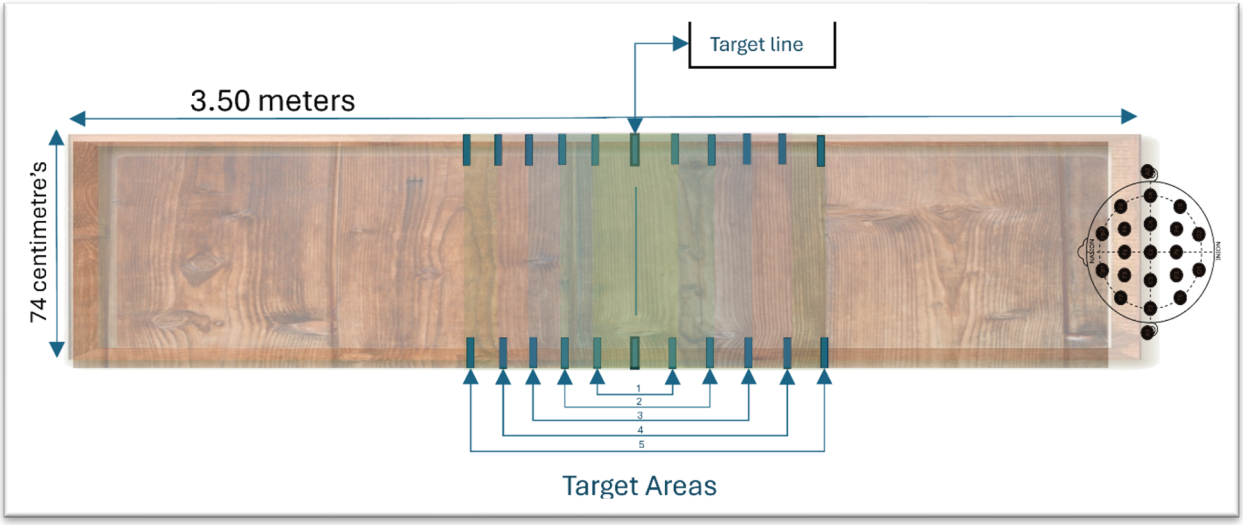

Figure 3. Layout displaying the target areas for five training sessions.

On Day 1, participants in each group completed one block of 200 trials, whereas on Day 2, they completed two blocks of 200 trials separated by 15 minutes of rest and on Day 3 they completed a further two blocks of 200 trials separated by 15 minutes of rest. On Day 4, participants completed a posttest consisting of 20 trials and a transfer test consisting of 20 trials. During training sessions, the number of successful and unsuccessful shuffles were manually recorded. A successful trial was

deemed to be one in which the disc stopped in the designated target area (between the lines), whereas an unsuccessful trial was deemed to be any trial in which the disc stopped outside the designated target area (or not on either line).

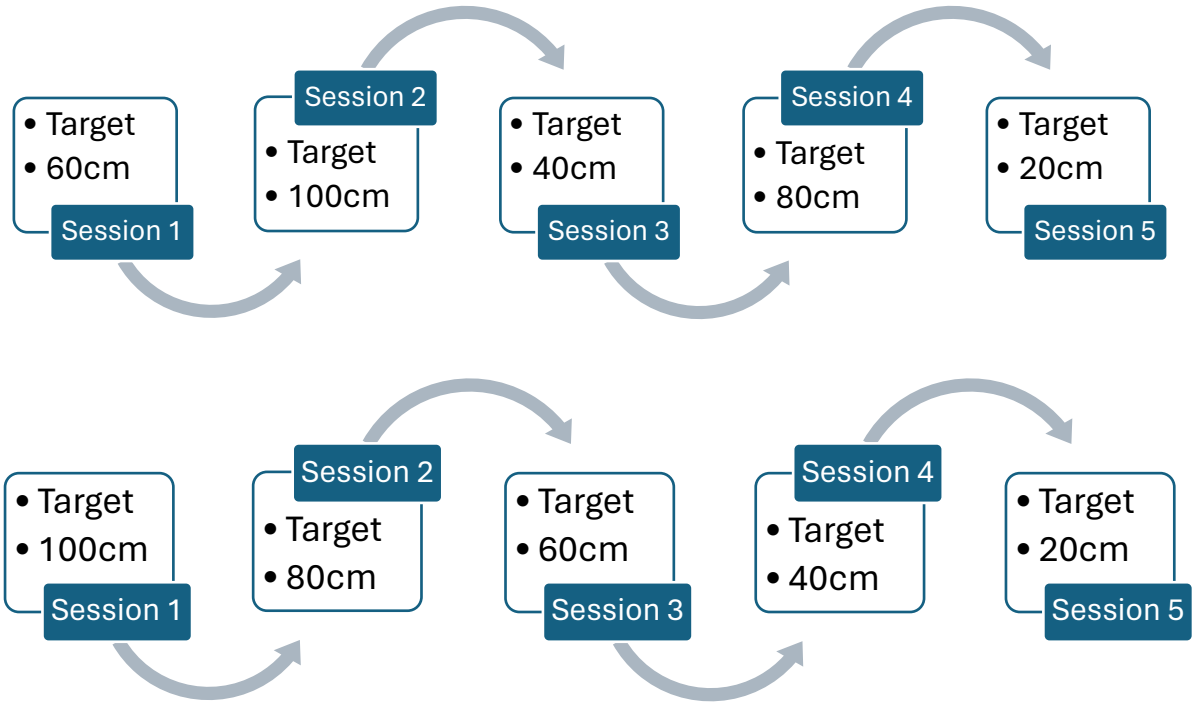

Figure 4. Order of distances from which participants completed each block of trials in the Errorless and Errorful Training conditions. Top row: Errorful; bottom row: Errorless

3.4.3. Posttest and Transfer Test

On the final day of testing (Day 4), the setup matched Day 1 in order to conduct baseline EEG measurements for the Posttest and Transfer Test. Baseline recordings were again completed with the eyes open for 30s and closed for 30s. This was followed by a posttest of 20 shuffles directed to reach the target line as accurately as possible. Finally, a transfer task was conducted, in which the participants completed 20 shuffles during which they hit the disc towards the target line as

accurately as possible with the rounded end of the multi-curved spatula. For both the Posttest and the Transfer test, the distance between the final position of the disc and the target line was recorded.

3.5. Analysis

3.5.1. Electroencephalography

EEG signals captured during the baselines were processed offline with EEGLAB software (Delorme & Makeig, 2004)running on MATLAB (Mathwork, Inc., USA version 2023b) to compute the connectivity measure. The EEG data was referenced to the average, band pass filtered (1-30Hz band pass filter), de-trended and a baseline correction was performed based on the average. The signals were then subjected to a threshold-based artefact removal procedure, where any 250-ms window containing signal fluctuations exceeding ±150 μV was rejected (ERPLAB Toolbox)(Lopez-Calderon & Luck, 2014). The total of 30 seconds was reduced to 22 seconds, due to the artefact's removal rejection. Independent Component Analyses (ICA) were then performed via the MARA ("Multiple Artifact Rejection Algorithm") to identify and remove any remaining artefacts and non-neural activity (e.g., eye-blinks) from the signal(Winkler et al., 2014; Winkler et al., 2011) . The alpha frequency band (8–12 Hz) was adjusted for each participant based on their individual alpha frequency (IAF) peak, determined from the baseline measure {IAF toolbox, Corcoran et al. (2018). Phase angles were obtained from the time frequency analysis and were used to compute intersite phase clustering connectivity (ISPC, Cohen, 2014)} between the electrode pairs in the beta frequency band for 22 seconds with eyes closed. We calculated the $ISPC_{time}$ using the following function:

$$ISPC_{xy}(f) = \left| n^{-1} \sum_{t=1}^{n} e^{i(\theta_x(tf)-\theta_y(tf))} \right|$$

N is the number of data points; i is the imaginary operator; θ_x and θ_y are the phase angles of the recorded signal at two different scalp locations; t is the time point and f is the frequency bin. The $e^{i(\theta_x(tf)-\theta_y(tf))}$ represents the complex vector with magnitude 1 and angle θ_x - θ_y ; $n^{-1} \sum_{t=1}^{n}$ (.) denotes averaging over time points, and |.| is the module of the averaged vector (Cohen, 2014; Lachaux et al., 1999). ISPC is given as a value between 0 (no functional connection) and 1 (perfect functional connection). Finally, values were Z-transformed (inverse hyperbolic tangent) to ensure normal distribution (Gallicchio et al., 2016)

3.5.2. Statistical analysis strategy

One participant was excluded from analysis due to a misunderstanding of the instructions that were provided. A further 8 participants were excluded from analysis because independent component analysis (ICA) revealed too many artifacts from the EEG recordings. Consequently, data was processed for 15 participants (errorless learning = 7; errorful learning = 8). EEG data were recorded at baseline prior to the pretest, posttest and the transfer test in order to determine whether implicit and explicit motor learning had a differential effect on brain plasticity. Three-way analysis of variance (Group: Errorless/Errorful x Baseline: Pre-/Post- x Electrode Pairs: Cz-T7, Cz-F7, C3-T7, C3-F7, C4-T7, and C4-F7) with repeated measures on the Baseline connectivity was used to examine changes in plasticity. Follow-up testing was conducted using pairwise comparisons. The mean number of errors during training phase were examined using a two-way analysis of variance (Group: Errorless/Errrorful x Session: 1 to 5) with repeated measures on the Session factor. Follow-up analysis was conducted using pairwise comparisons. The mean absolute accuracy during the pretest, the posttest and the transfer test were also examined using a two-way analysis

of variance (Group: Errorless/Errorful x Test: Pretest/Posttest/Transfer) with repeated measures on the Test factor. Follow-up analysis was conducted using pairwise comparisons.

Chapter 4: Results

4.1. Errors

Figure 5 displays the mean number of errors as a percentage, for the Errorful group and the Errorless group across the five training sessions (200 trials per session). Mauchly's Test of Sphericity was non-significant (p = .598), suggesting equivalence of variances in the groups. A two-way analysis of variance with repeated measures on the Session factor revealed the main effect of training Session, F (4,52) = 224.61, p < .001, ηp^2 = .945. and a Session x Group interaction, F (4,52) = 74.70, p < .001, ηp^2 = .85. The main effect of Group was not evident, F (1,13) = .21, p = .658, ηp^2 = .16. The interaction is explained by extreme changes in the number of errors made by the participants in the errorful condition compared to the errorless condition as they switched between random distances.

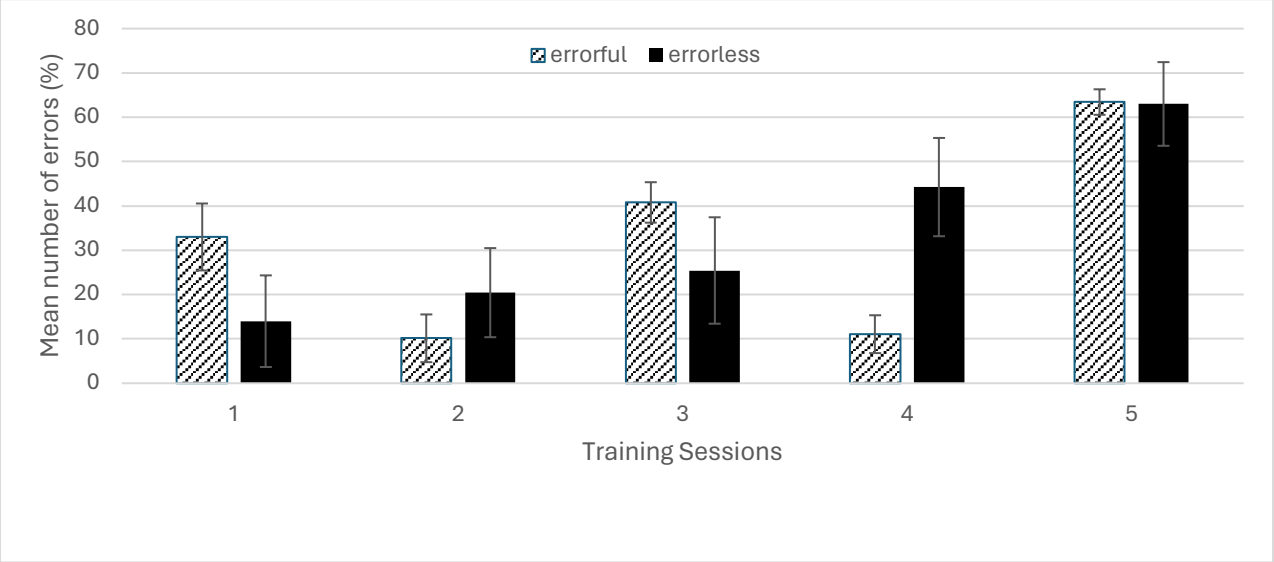

Figure 5. Mean number of errors (%) by participants over five training sessions in both the errorless and errorful conditions.

4.2. Performance

Figure 6 displays the mean scores in Errorless and Errorful conditions during the pretest, posttest, and transfer test. A two-way analysis of variance with repeated measure on the test factor revealed a main effect of Test, $F(2, 26) = 18.08$, $p < .001$, $\eta p^2 = .582$. However, the main effect of Group was not evident, $F(1,13) = .009$, $p = .926$, $\eta p^2 = .001$. Nor was there a Test by Group interaction, $F(2,26) = .38$, $p = .687$, $\eta p^2 = .028$. Follow up testing using pairwise comparisons revealed that for the main effect of Test accuracy was significantly higher (i.e., lower absolute distance from the target line) in the posttest compared to the pretest, $p < .001$, but not in the pretest compared to the transfer test, $p = .06$. Accuracy in the posttest was significantly higher than in the transfer test, $p = .024$.

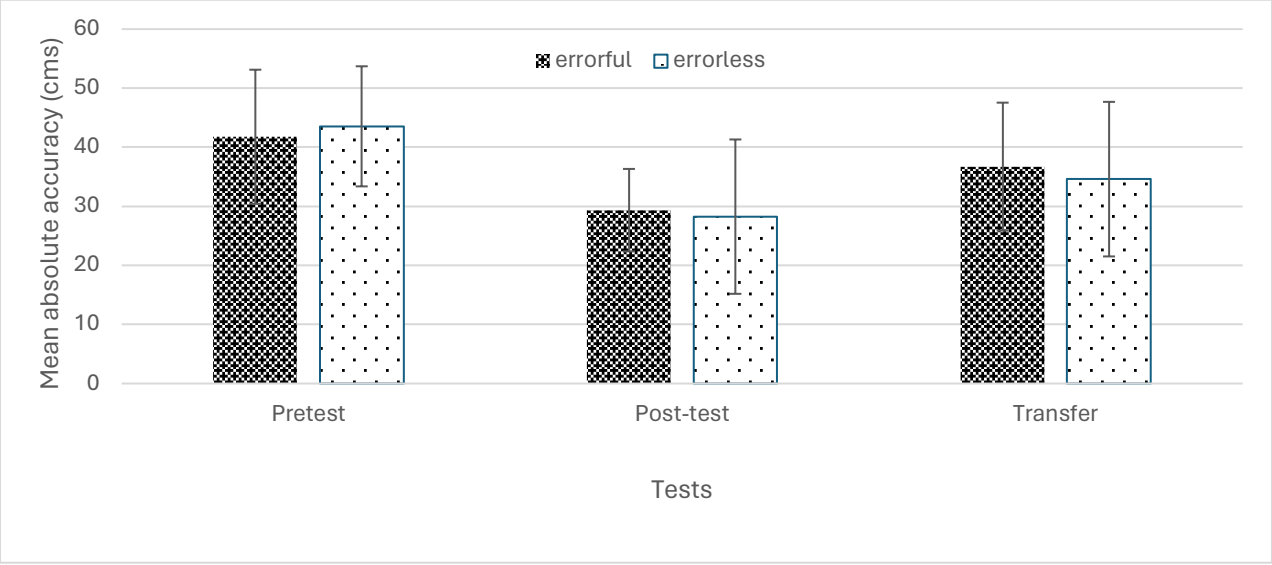

Figure 6. Mean absolute distance of the disc from the target line in the pretest, posttest, and transfer test in both the errorful and errorless conditions.

4.3. Resting State Beta Connectivity

A three-way ANOVA (Group x Test x Electrode Pairs) with repeated measures on the Test factor did not reveal a Test x Electrodes Pair x Group interaction for Beta band connectivity, F (5,65) = 1.722, p = .142, ηp^2 = .117. Interactions were not evident for Test x Group, F (1,65) = .719, p = .412, ηp^2 = .052, or Test x Electrode Pairs, F (5,65) = 2.182, p = .067, ηp^2 = .144.

However, an interaction was evident for Group x Electrode Pairs, F (5,65) = 3.989, p = .003, ηp^2 = .235 (see Figure 9 & 10). Pairwise analysis was used to further examine the Group x Electrode Pairs interaction, revealing that connectivity was higher in the Errorless group for Cz-F7 (p = .017) but lower for C3-T7 (p = .019). No effects were evident for all the other connectivity: CzT7, C3F7, C4T7, C4F7 (all p's > .05). Main effects were not evident for Test, F (1,65) = 0.675, p = .426, ηp^2 = .049, or for Group, F (1,13) = 0.583, p = .459, ηp^2 = 0.043, or for Electrode Pairs, F (5,65) = 1.16, p = .338, ηp^2 = .082.

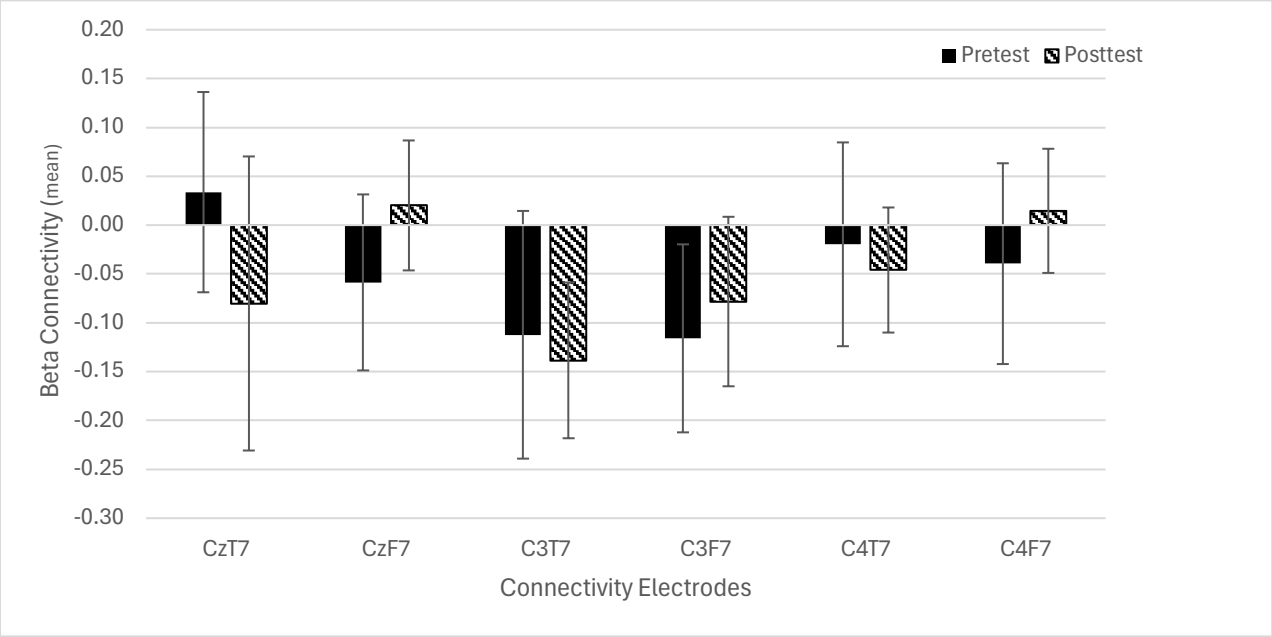

Figure 7. Beta band connectivity for pretest and posttest in errorless condition

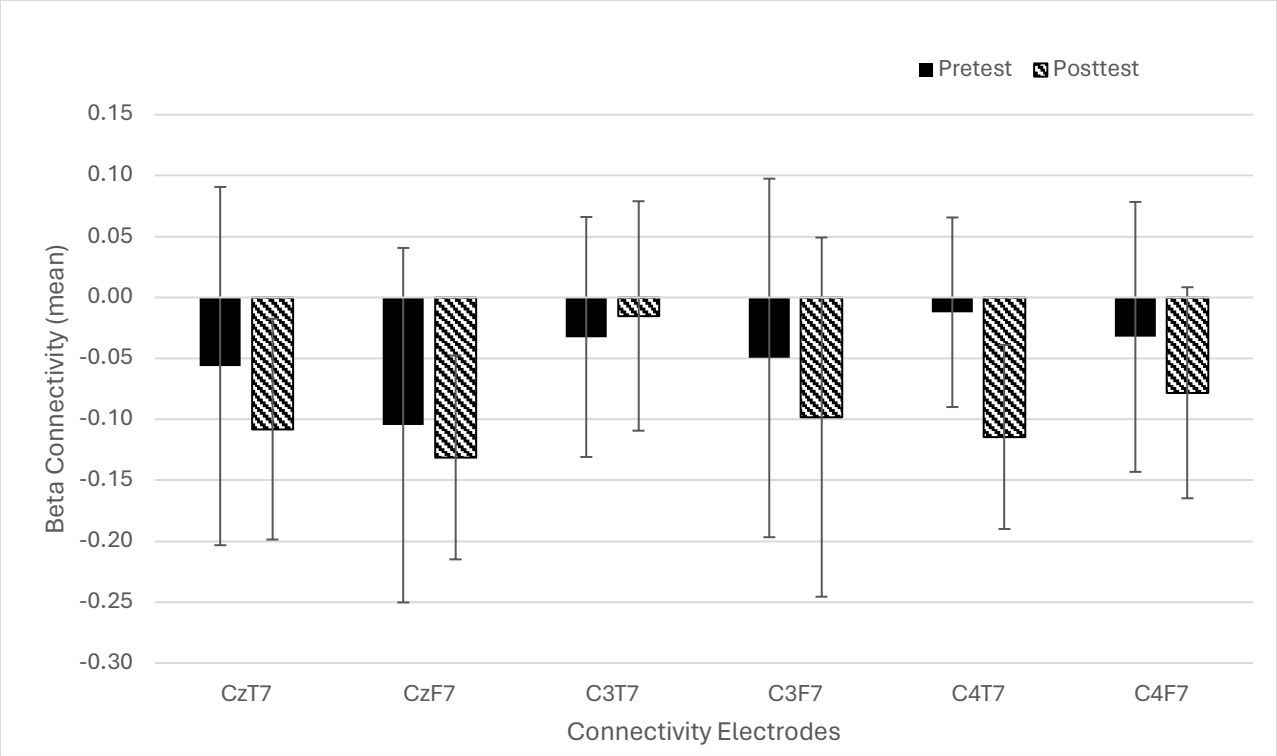

Figure 8. Beta band connectivity for pretest and posttest in errorful condition

Chapter 5: Discussion

Two protocols were developed to facilitate the learning of a simple shuffleboard task: one focused on errorless learning and the other on errorful learning, similar to the approach used by Capio et al. (2013) to promote fundamental skill learning (i.e., overhead throwing, which is similar to shuffling). In this experiment, neuroplasticity was examined in both implicit (incrementally larger, easier target areas to smaller, more difficult target areas) and explicit learning strategies (random target areas). After implementing both protocols, a transfer test was conducted to assess behavioral changes.

The behavioral results indicated that learning occurred, as participants in both the errorless and errorful learning conditions showed improved accuracy on the posttest and the transfer test compared to the pretest. However, over the practice sessions, the overall errors created by the participants were similar for both the errorless learning protocol (33.42 ± 10.58) and the errorful learning protocol (31.68 ± 4.92). The lack of differences in errors between groups suggests that implicit motor learning did not occur in the errorless group. Evidence that this is likely, comes from subjective responses by participants after the learning phase to task-specific questions adapted from the Movement Specific Reinvestment Scale (see Appendix 5.1, 5.3) (Masters et al., 2005), which were designed to assess conscious engagement in the task. The Movement Specific Reinvestment Scale has been shown to be a reliable and valid tool for assessing conscious engagement in learning contexts (Kal et al., 2016; Masters et al., 1993). Responses to the adapted questions suggested relatively elevated levels of conscious awareness of performing the task in both the errorless learning group (M=19.07/30) and the errorful learning group (M=22.70/ 30).

The analysis of learning outcomes, measured by the mean accuracy of disc distance from the target, revealed several important insights. Notably, mean accuracy improved from the pretest to both the posttest and transfer test, indicating that participants successfully learned the task across these phases. In analysis, accuracy in the posttest was significantly higher than in the transfer test, p =.024. The decline in accuracy during the transfer test indicates that participants faced challenges in applying their learned skills in a new context, suggesting a disruption in the learning process. This finding contrasts with the research by Capio et al. (2013), which demonstrated that errorless learning is typically less affected by pressure. Their results suggest that individuals trained using errorless methods can maintain performance even in challenging situations. We anticipated that the errorless group would show less decline in accuracy during the transfer task; however, despite a positive correlation, the results were not significant enough to support this expectation. While participants initially understood the task, they encountered challenges in applying their skills to a different context during the transfer test. This observation aligns with Gass's (1999) theory of transfer, which addresses the concept of negative transfer. Despite potentially effective training, participants struggled to transition to the new task. This suggests that while the errorless learning method demonstrated some benefits, it was insufficient to prevent a decline in accuracy when faced with a more challenging context.

As per the literature (Capio et al., 2013; Schmidt & Lee, 2011), the implicit motor learning group should have adapted better to the transfer task, potentially due to their more efficient learning approach facilitating smoother transitions to new tasks, however the participants were not able to learn via implicit learning, hence we did not find anything significant on analysis. Also, the statistical evidence for this adaptation (i.e., there was no interaction) was not robust, primarily due to a limited number of participants.

Furthermore, it has been evident that the Primary Motor Cortex (M1) is known to play a critical role in motor learning and can be influenced by practice (Gentili et al., 2015; Krause et al., 2016; Mehrkanoon et al., 2016; Pollok et al., 2014). Hence, in our study, we investigated resting-state beta connectivity in electrodes representing the Primary Motor Cortex and the left superior temporal gyrus, specifically Cz, C3, C4, T7, and F7 inspired by the work of Sugata et al. (2020) which found that resting-state beta connectivity between M1 and the left superior temporal gyrus to be greater in individuals who learn a sequence effectively compared to those who struggle.

We anticipated observing increased resting-state connectivity in the beta band between the M1 regions (Cz, C3, and C4) and the left superior temporal gyrus regions (T7 and F7). Specifically, we expected to see positive changes in connectivity between the following pairs: Cz-T7, Cz-F7, C3-T7, C3-F7, C4-T7, and C4-F7. However, our three-way ANOVA revealed no significant interaction between Test, Electrodes, and Group for beta band connectivity. Similarly, there were no significant interactions for Test x Group or Test x Electrodes.

Notably, we did find an interaction between Group and Electrodes ($p = .003$). Follow-up analysis showed higher connectivity in the Errorless group, but lower connectivity for Cz-F7 ($p = .017$) and C3-T7 ($p = .019$). No significant effects were found for the other connectivity pairs (all p's $> .05$). Although the Errorless group demonstrated higher overall connectivity, the primary connectivity we investigated showed a reverse effect, which contradicts the findings of Sugata et al. (2020). Overall, our results indicate that no significant beta connectivity was observed in either group, which aligns with the behavioral findings.

5.1. Conclusion

We anticipated stronger effects for both behavioral and neural measures, but the results were inconsistent with our expectations. The lack of significant error rates stemmed from the absence of implicit learning in the errorless condition. Additionally, many participants were excluded due to poor EEG data quality, which affected the overall sample size and reliability of the findings. While there were trends indicating some learning and adaptation, the limited data temper our conclusions, highlighting the need for further research with a larger sample to explore the implications of errorless versus errorful learning strategies on neuro-adaptability.

Both errorless and errorful learning improved accuracy in posttests compared to pretests, indicating learning. However, the absence of significant differences in error rates or verbal protocols suggests that implicit learning did not occur. The drop in accuracy from the posttest to the transfer test highlights challenges in applying learned skills in new contexts, pointing to negative transfer, especially given the lack of true implicit learning to facilitate positive transfer. Additionally, EEG data showed no significant differences in beta connectivity, reinforcing this conclusion. These limitations underscore the need for more rigorous studies to better understand different learning strategies.

5.2. Future Scope

The findings from this study suggest several avenues for future research into errorless and errorful learning strategies to fully explore their implications on neuro-adaptability. First, larger sample sizes are essential to enhance statistical power and robustness, particularly regarding the effects on performance and neuroplasticity. Longitudinal studies could provide insights into learning

retention and transfer over time, while variations in task complexity may help clarify when each strategy is most effective.

Incorporating additional neurophysiological measurements, such as functional MRI or real-time EEG during task performance, could deepen our understanding of the neural mechanisms involved. Investigating individual differences, such as prior experience and learning styles, may also optimize learning outcomes.

Moreover, examining the practical applications of these strategies in real-world contexts, alongside the impact of feedback mechanisms, could yield valuable insights. Finally, comparative studies across different motor tasks could reveal whether the effectiveness of these learning methods is universally applicable or context dependent. Addressing these areas will contribute to a comprehensive understanding of the dynamics of skill acquisition and the neuroadaptive processes at play.

Chapter 6: References

Adams, J. A. (1971). A Closed-Loop Theory of Motor Learning. *Journal of Motor Behavior*, *3*(2), 111-150. https://doi.org/10.1080/00222895.1971.10734898

Amo, C., De Santiago, L., Zarza Luciáñez, D., León Alonso-Cortés, J. M., Alonso-Alonso, M., Barea, R., & Boquete, L. (2017). Induced gamma band activity from EEG as a possible index of training-related brain plasticity in motor tasks. *PLoS One*, *12*(10), e0186008.

Ayoub, A. E., & Rakic, P. (2015). Neuronal misplacement in schizophrenia. *Biol Psychiatry*, *77*(11), 925-926. https://doi.org/10.1016/j.biopsych.2015.03.022

Baars, B. J. (1997). In the theatre of consciousness: Global workspace theory, a rigorous scientific theory of consciousness. *Journal of Consciousness Studies*, *4*(4), 292-309.

Baddeley, A. (2000). The episodic buffer: A new component of working memory? *Trends in Cognitive Sciences*, *4*(11), 417-423. https://doi.org/10.1016/S1364-6613(00)01538-2

Baddeley, A. (2012). Working memory: theories, models, and controversies. *Annu Rev Psychol*, *63*, 1-29. https://doi.org/10.1146/annurev-psych-120710-100422

Baddeley, A. D. (2002). Is working memory still working? *European Psychologist*, *7*(2), 85-97. https://doi.org/10.1027/1016-9040.7.2.85

Baddeley, A. D., & Hitch, G. (1974). Working Memory. In G. H. Bower (Ed.), *Psychology of Learning and Motivation* (Vol. 8, pp. 47-89). Academic Press. https://doi.org/https://doi.org/10.1016/S0079-7421(08)60452-1

Bienenstock, E. L., Cooper, L. N., & Munro, P. W. (1982). Theory for the development of neuron selectivity: orientation specificity and binocular interaction in visual cortex. *J Neurosci*, *2*(1), 32-48. https://doi.org/10.1523/jneurosci.02-01-00032.1982

Bootsma, J. M., Caljouw, S. R., Veldman, M. P., Maurits, N. M., Rothwell, J. C., & Hortobágyi, T. (2021). Neural correlates of motor skill learning are dependent on both age and task difficulty. *Frontiers in aging neuroscience*, *13*, 643132.

Boyd, L. A., & Winstein, C. J. (2004). Cerebellar Stroke Impairs Temporal but Not Spatial Accuracy during Implicit Motor Learning. *Neurorehabilitation and Neural Repair*, *18*(3), 134-143. https://doi.org/10.1177/0888439004269072

Brockmole, J. R., & Logie, R. H. (2013). Age-related change in visual working memory: A study of 55,753 participants aged 8–75. *Frontiers in Psychology*, *4*. https://doi.org/10.3389/fpsyg.2013.00012

Butt, M., Naghdy, G., Naghdy, F., Murray, G., & Du, H. (2020). Patient-Specific Robot-Assisted Stroke Rehabilitation Guided by EEG - A Feasibility Study. *Annu Int Conf IEEE Eng Med Biol Soc*, *2020*, 2841-2844. https://doi.org/10.1109/embc44109.2020.9175459

Capio, C. M., Poolton, J. M., Sit, C. H. P., Holmstrom, M., & Masters, R. S. W. (2013). Reducing errors benefits the field-based learning of a fundamental movement skill in children. *Scandinavian Journal of Medicine & Science in Sports*, *23*(2), 181-188. https://doi.org/https://doi.org/10.1111/j.1600-0838.2011.01368.x

Chang, Y. (2014). Reorganization and plastic changes of the human brain associated with skill learning and expertise. *Frontiers in Human Neuroscience*, *8*. https://doi.org/10.3389/fnhum.2014.00035

Chen, R., Classen, J., Gerloff, C., Celnik, P., Wassermann, E. M., Hallett, M., & Cohen, L. G. (1997). Depression of motor cortex excitability by low-frequency transcranial magnetic stimulation. *Neurology*, *48*(5), 1398-1403. https://doi.org/10.1212/wnl.48.5.1398

Cohen, M. X. (2014). *Analyzing neural time series data: Theory and practice*. MIT Press.

Collingridge, G. L., & Bliss, T. V. (1987). NMDA receptors: Their role in long-term potentiation. *Trends in Neurosciences*, *10*(7), 288-293. https://doi.org/10.1016/0166-2236(87)90175-5

Collingridge, G. L., & Bliss, T. V. (1995). Memories of NMDA receptors and LTP. *Trends Neurosci*, *18*(2), 54-56.

Corcoran, A. W., Alday, P. M., Schlesewsky, M., & Bornkessel‐Schlesewsky, I. (2018). Toward a reliable, automated method of individual alpha frequency (IAF) quantification. *Psychophysiology*, *55*(7), e13064.

Cramer, S. C., Sur, M., Dobkin, B. H., O'Brien, C., Sanger, T. D., Trojanowski, J. Q., Rumsey, J. M., Hicks, R., Cameron, J., Chen, D., Chen, W. G., Cohen, L. G., deCharms, C., Duffy, C. J., Eden, G. F., Fetz, E. E., Filart, R., Freund, M., Grant, S. J., . . . Vinogradov, S. (2011). Harnessing neuroplasticity for clinical applications. *Brain*, *134*(Pt 6), 1591-1609. https://doi.org/10.1093/brain/awr039

Dancause, N., Barbay, S., Frost, S. B., Plautz, E. J., Chen, D., Zoubina, E. V., Stowe, A. M., & Nudo, R. J. (2005). Extensive cortical rewiring after brain injury. *J Neurosci*, *25*(44), 10167-10179. https://doi.org/10.1523/jneurosci.3256-05.2005

Dayan, E., & Cohen, Leonardo G. (2011). Neuroplasticity Subserving Motor Skill Learning. *Neuron*, *72*(3), 443-454. https://doi.org/https://doi.org/10.1016/j.neuron.2011.10.008

Delorme, A., & Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J Neurosci Methods*, *134*(1), 9-21. https://doi.org/10.1016/j.jneumeth.2003.10.009

Diamond, A. (1985). Development of the Ability to Use Recall to Guide Action, as Indicated by Infants' Performance on AB̄. *Child Development*, *56*(4), 868-883. https://doi.org/10.2307/1130099

Doyon, J., & Benali, H. (2005). Reorganization and plasticity in the adult brain during learning of motor skills. *Current Opinion in Neurobiology*, *15*(2), 161-167. https://doi.org/https://doi.org/10.1016/j.conb.2005.03.004

Doyon, J., Penhune, V., & Ungerleider, L. G. (2003). Distinct contribution of the cortico-striatal and cortico-cerebellar systems to motor skill learning. *Neuropsychologia*, *41*(3), 252-262.

Doyon, J., Ungerleider, L., Squire, L., & Schacter, D. (2002). Neuropsychology of memory. In: Guilford Press New York:.

Dyck, S., & Klaes, C. (2024). Training-related changes in neural beta oscillations associated with implicit and explicit motor sequence learning. *Sci Rep*, *14*(1), 6781. https://doi.org/10.1038/s41598-024-57285-7

Fitts, P. M., & Posner, M. I. (1967). *Human performance*. Brooks/Cole.

Gallicchio, G., Cooke, A., & Ring, C. (2016). Lower left temporal-frontal connectivity characterizes expert and accurate performance: High-alpha T7-Fz connectivity as a marker of conscious processing during movement. *Sport, Exercise, and Performance Psychology*, *5*(1), 14-24. https://doi.org/http://dx.doi.org/10.1037/spy0000055

Gass, M. (1999). Transfer of Learning in Adventure Programming.

Geinisman, Y., Berry, R. W., Disterhoft, J. F., Power, J. M., & Van der Zee, E. A. (2001). Associative Learning Elicits the Formation of Multiple-Synapse Boutons. *The Journal of Neuroscience*, *21*(15), 5568-5573. https://doi.org/10.1523/jneurosci.21-15-05568.2001

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. https://doi.org/https://doi.org/10.1016/j.biopsycho.2014.12.003

Giaquinto, S., Cobianchi, A., Macera, F., & Nolfe, G. (1994). EEG recordings in the course of recovery from stroke. *Stroke*, *25*(11), 2204-2209. https://doi.org/10.1161/01.str.25.11.2204

Gilchrist, A. L., Cowan, N., & Naveh-Benjamin, M. (2008). Working memory capacity for spoken sentences decreases with adult ageing: Recall of fewer but not smaller chunks in older adults. *Memory*, *16*(7), 773-787.

Goh, H.-T., Sullivan, K. J., Gordon, J., Wulf, G., & Winstein, C. J. (2012). Dual-task practice enhances motor learning: a preliminary investigation. *Experimental Brain Research*, *222*(3), 201-210. https://doi.org/10.1007/s00221-012-3206-5

Gong, A., Nan, W., Yin, E., Jiang, C., & Fu, Y. (2020). Efficacy, Trainability, and Neuroplasticity of SMR vs. Alpha Rhythm Shooting Performance Neurofeedback Training. *Front Hum Neurosci*, *14*, 94. https://doi.org/10.3389/fnhum.2020.00094

Gould, E., Beylin, A., Tanapat, P., Reeves, A., & Shors, T. J. (1999). Learning enhances adult neurogenesis in the hippocampal formation. *Nat Neurosci*, *2*(3), 260-265. https://doi.org/10.1038/6365

Gucciardi, D. F., & Dimmock, J. A. (2008). Choking under pressure in sensorimotor skills: Conscious processing or depleted attentional resources? *Psychology of Sport and Exercise*, *9*(1), 45-59. https://doi.org/https://doi.org/10.1016/j.psychsport.2006.10.007

Hebb, D. O. (2005). *The organization of behavior: A neuropsychological theory*. Psychology press.

Hikosaka, O., Nakamura, K., Sakai, K., & Nakahara, H. (2002). Central mechanisms of motor skill learning. *Curr Opin Neurobiol*, *12*(2), 217-222. https://doi.org/10.1016/s0959-4388(02)00307-0

Huang, Z. J., Kirkwood, A., Pizzorusso, T., Porciatti, V., Morales, B., Bear, M. F., Maffei, L., & Tonegawa, S. (1999). BDNF Regulates the Maturation of Inhibition and the Critical Period of Plasticity in Mouse Visual Cortex. *Cell*, *98*(6), 739-755. https://doi.org/https://doi.org/10.1016/S0092-8674(00)81509-3

Innocenti, G., Frost, D., & Illes, J. (1985). Maturation of visual callosal connections in visually deprived kittens: a challenging critical period. *Journal of neuroscience*, *5*(2), 255-267.

Innocenti, G. M. (1995). Exuberant development of connections, and its possible permissive role in cortical evolution. *Trends in Neurosciences*, *18*(9), 397-402. https://doi.org/https://doi.org/10.1016/0166-2236(95)93936-R

Innocenti, G. M., Dyrby, T. B., Andersen, K. W., Rouiller, E. M., & Caminiti, R. (2016). The Crossed Projection to the Striatum in Two Species of Monkey and in Humans: Behavioral and Evolutionary Significance. *Cerebral Cortex*, *27*(6), 3217-3230. https://doi.org/10.1093/cercor/bhw161

Ito, M. (2002). Historical review of the significance of the cerebellum and the role of Purkinje cells in motor learning. *Annals of the New York Academy of Sciences*, *978*(1), 273-288.

Jahani, A., Schwey, A., Bernier, P.-M., & Malfait, N. (2020). Spatially Distinct Beta-Band Activities Reflect Implicit Sensorimotor Adaptation and Explicit Re-aiming Strategy. *The Journal of Neuroscience*, *40*(12), 2498-2509. https://doi.org/10.1523/jneurosci.1862-19.2020

James, W. (1890). The principles of psychology. *Henry Holt*.

Jiménez, L., & Méndez, C. (2001). Implicit Sequence Learning with Competing Explicit Cues. *The Quarterly Journal of Experimental Psychology Section A*, *54*(2), 345-369. https://doi.org/10.1080/713755964

Kal, E., Houdijk, H., Van Der Wurff, P., Groet, E., Van Bennekom, C., Scherder, E., & Van der Kamp, J. (2016). The inclination for conscious motor control after stroke: Validating the Movement-Specific Reinvestment Scale for use in inpatient stroke patients. *Disability and rehabilitation*, *38*(11), 1097-1106.

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain Res Brain Res Rev*, *29*(2-3), 169-195. https://doi.org/10.1016/s0165-0173(98)00056-3

Kolb, B., & Gibb, R. (2011). Brain plasticity and behaviour in the developing brain. *J Can Acad Child Adolesc Psychiatry*, *20*(4), 265-276.

Konorski, J. (1948). *Conditioned reflexes and neuron organization*. Cambridge University Press.

Korka, B., Will, M., Avci, I., Dukagjini, F., & Stenner, M. P. (2023). Strategy-based motor learning decreases the post-movement β power. *Cortex*, *166*, 43-58. https://doi.org/10.1016/j.cortex.2023.05.002

Krause, V., Meier, A., Dinkelbach, L., & Pollok, B. (2016). Beta band transcranial alternating (tACS) and direct current stimulation (tDCS) applied after initial learning facilitate

retrieval of a motor sequence [Article]. *Frontiers in Behavioral Neuroscience*, *10*(JAN), Article 4. https://doi.org/10.3389/fnbeh.2016.00004

Lachaux, J. P., Rodriguez, E., Martinerie, J., & Varela, F. J. (1999). Measuring phase synchrony in brain signals. *Human brain mapping*, *8*(4), 194-208. https://doi.org/10.1002/(SICI)1097-0193(1999)8:4<194::AID-HBM4>3.0.CO;2-C

Landi, S. M., Baguear, F., & Della-Maggiore, V. (2011). One Week of Motor Adaptation Induces Structural Changes in Primary Motor Cortex That Predict Long-Term Memory One Year Later. *The Journal of Neuroscience*, *31*(33), 11808-11813. https://doi.org/10.1523/jneurosci.2253-11.2011

Liao, C. M., & Masters, R. S. (2001). Analogy learning: a means to implicit motor learning. *J Sports Sci*, *19*(5), 307-319. https://doi.org/10.1080/02640410152006081

Light, R. J., Singer, J. D., & Willett, J. B. (1990). *By design: Planning research on higher education*. Harvard University Press.

Lopez-Calderon, J., & Luck, S. J. (2014). ERPLAB: an open-source toolbox for the analysis of event-related potentials. *Front Hum Neurosci*, *8*, 213. https://doi.org/10.3389/fnhum.2014.00213

Lucassen, P. J., Fitzsimons, C. P., Salta, E., & Maletic-Savatic, M. (2020). Adult neurogenesis, human after all (again): Classic, optimized, and future approaches. *Behav Brain Res*, *381*, 112458. https://doi.org/10.1016/j.bbr.2019.112458

Manginelli, A. A., Langer, N., Klose, D., & Pollmann, S. (2013). Contextual cueing under working memory load: Selective interference of visuospatial load with expression of learning. *Attention, Perception, & Psychophysics*, *75*(6), 1103-1117. https://doi.org/10.3758/s13414-013-0466-5

Masters, R., Eves, F., Morris, T., Terry, P., & Gordon, S. (2005). Proceedings of the ISSP 11th World Congress of Sport Psychology. In: International Society of Sports Psychology, Sydney, Australia.

Masters, R. S., Polman, R., & Hammond, N. (1993). 'Reinvestment': A dimension of personality implicated in skill breakdown under pressure. *Personality and individual differences*, *14*(5), 655-666.

Masters, R. S. W. (1992). Knowledge, knerves and know-how: The role of explicit versus implicit knowledge in the breakdown of a complex motor skill under pressure. *British Journal of Psychology*, *83*(3), 343-358. https://doi.org/https://doi.org/10.1111/j.2044-8295.1992.tb02446.x

Maxwell, J. P., Masters, R. S., & Eves, F. F. (2000). From novice to no know-how: a longitudinal study of implicit motor learning. *J Sports Sci*, *18*(2), 111-120. https://doi.org/10.1080/026404100365180

Maxwell, J. P., Masters, R. S. W., Kerr, E., & Weedon, E. (2001). The implicit benefit of learning without errors. *The Quarterly Journal of Experimental Psychology Section A*, *54*(4), 1049-1068. https://doi.org/10.1080/713756014

May, A. (2011). Experience-dependent structural plasticity in the adult human brain. *Trends in Cognitive Sciences*, *15*(10), 475-482. https://doi.org/10.1016/j.tics.2011.08.002

Meehan, S. K., Randhawa, B., Wessel, B., & Boyd, L. A. (2011). Implicit sequence-specific motor learning after subcortical stroke is associated with increased prefrontal brain activations: an fMRI study. *Hum Brain Mapp*, *32*(2), 290-303. https://doi.org/10.1002/hbm.21019

Mehrkanoon, S., Boonstra, T. W., Breakspear, M., Hinder, M., & Summers, J. J. (2016). Upregulation of cortico-cerebellar functional connectivity after motor learning.

Neuroimage, *128*, 252-263. https://doi.org/https://doi.org/10.1016/j.neuroimage.2015.12.052

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, *63*(2), 81.

Morris, P. R., & Whiting, H. T. A. (1971). Motor impairment and compensatory education. *(No Title)*.

Murphy, T. H., & Corbett, D. (2009). Plasticity during stroke recovery: from synapse to behaviour. *Nat Rev Neurosci*, *10*(12), 861-872. https://doi.org/10.1038/nrn2735

Nudo, R. J., Wise, B. M., SiFuentes, F., & Milliken, G. W. (1996). Neural substrates for the effects of rehabilitative training on motor recovery after ischemic infarct. *Science*, *272*(5269), 1791-1794. https://doi.org/10.1126/science.272.5269.1791

Oberman, L., & Pascual-Leone, A. (2013). Changes in plasticity across the lifespan: cause of disease and target for intervention. *Prog Brain Res*, *207*, 91-120. https://doi.org/10.1016/b978-0-444-63327-9.00016-3

Orrell, A. J., Masters, R. S. W., & Eves, F. F. (2009). Reinvestment and Movement Disruption Following Stroke. *Neurorehabilitation and Neural Repair*, *23*(2), 177-183. https://doi.org/10.1177/1545968308317752

Pascual-Leone, A., Amedi, A., Fregni, F., & Merabet, L. B. (2005). The plastic human brain cortex. *Annu Rev Neurosci*, *28*, 377-401. https://doi.org/10.1146/annurev.neuro.27.070203.144216

Pekna, M., Pekny, M., & Nilsson, M. (2012). Modulation of neural plasticity as a basis for stroke rehabilitation. *Stroke*, *43*(10), 2819-2828. https://doi.org/10.1161/strokeaha.112.654228

Pfurtscheller, G., & Lopes da Silva, F. H. (1999). Event-related EEG/MEG synchronization and desynchronization: basic principles. *Clin Neurophysiol*, *110*(11), 1842-1857. https://doi.org/10.1016/s1388-2457(99)00141-8

Poldrack, R. A., Clark, J., Paré-Blagoev, E. J., Shohamy, D., Creso Moyano, J., Myers, C., & Gluck, M. A. (2001). Interactive memory systems in the human brain. *Nature*, *414*(6863), 546-550. https://doi.org/10.1038/35107080

Pollok, B., Latz, D., Krause, V., Butz, M., & Schnitzler, A. (2014). Changes of motor-cortical oscillations associated with motor learning. *Neuroscience*, *275*, 47-53. https://doi.org/https://doi.org/10.1016/j.neuroscience.2014.06.008

Ramscar, M., Hendrix, P., Shaoul, C., Milin, P., & Baayen, H. (2014). The myth of cognitive decline: non-linear dynamics of lifelong learning. *Top Cogn Sci*, *6*(1), 5-42. https://doi.org/10.1111/tops.12078

Reber, P. J., & Kotovsky, K. (1997). Implicit learning in problem solving: The role of working memory capacity. *Journal of Experimental Psychology: General*, *126*(2), 178-203. https://doi.org/10.1037/0096-3445.126.2.178

Rioult-Pedotti, M. S., Friedman, D., & Donoghue, J. P. (2000). Learning-induced LTP in neocortex. *Science*, *290*(5491), 533-536. https://doi.org/10.1126/science.290.5491.533

Rojas, G. M., Alvarez, C., Montoya, C. E., de la Iglesia-Vayá, M., Cisternas, J. E., & Gálvez, M. (2018). Study of Resting-State Functional Connectivity Networks Using EEG Electrodes Position As Seed. *Front Neurosci*, *12*, 235. https://doi.org/10.3389/fnins.2018.00235

Romero, S. G., McFarland, D. J., Faust, R., Farrell, L., & Cacace, A. T. (2008). Electrophysiological markers of skill-related neuroplasticity. *Biol Psychol*, *78*(3), 221-230. https://doi.org/10.1016/j.biopsycho.2008.03.014

Sagi, Y., Tavor, I., Hofstetter, S., Tzur-Moryosef, S., Blumenfeld-Katzir, T., & Assaf, Y. (2012). Learning in the fast lane: new insights into neuroplasticity. *Neuron*, *73*(6), 1195-1203. https://doi.org/10.1016/j.neuron.2012.01.025

Scerbo, M. W., Freeman, F. G., & Mikulka, P. J. (2003). A brain-based system for adaptive automation. *Theoretical Issues in Ergonomics Science*, *4*(1-2), 200-219.

Schendan, H. E., Searl, M. M., Melrose, R. J., & Stern, C. E. (2003). An FMRI study of the role of the medial temporal lobe in implicit and explicit sequence learning. *Neuron*, *37*(6), 1013-1025. https://doi.org/10.1016/s0896-6273(03)00123-5

Schmidt, R. A. (1975). A schema theory of discrete motor skill learning. *Psychological Review*, *82*(4), 225-260. https://doi.org/10.1037/h0076770

Schmidt, R. A., & Lee, T. D. (2011). *Motor control and learning: A behavioral emphasis, 5th ed*. Human Kinetics.

Shi, Y., Helou, G., Yan, L., Armus, L., Wu, Y., Papovich, C., & Stierwalt, S. (2011). Extended Schmidt law: role of existing stars in current star formation. *The Astrophysical Journal*, *733*(2), 87.

Shibasaki, H., Sadato, N., Lyshkow, H., Yonekura, Y., Honda, M., Nagamine, T., Suwazono, S., Magata, Y., Ikeda, A., Miyazaki, M., & et al. (1993). Both primary motor cortex and supplementary motor area play an important role in complex finger movement. *Brain*, *116 (Pt 6)*, 1387-1398. https://doi.org/10.1093/brain/116.6.1387

Shumway-Cook, A. (2007). Motor control: translating research into clinical practice. *Lippincoot Williams & Wilkins*.

Squire, L. R., Berg, D. K., Bloom, F. E., Lac, S. d., Ghosh, A., & Spitzer, N. C. (2012). Fundamental Neuroscience: Fourth Edition.

Sugata, H., Yagi, K., Yazawa, S., Nagase, Y., Tsuruta, K., Ikeda, T., Nojima, I., Hara, M., Matsushita, K., Kawakami, K., & Kawakami, K. (2020). Role of beta-band resting-state functional connectivity as a predictor of motor learning ability. *Neuroimage*, *210*, 116562. https://doi.org/https://doi.org/10.1016/j.neuroimage.2020.116562

Tamaki, M., Huang, T.-R., Yotsumoto, Y., Hämäläinen, M., Lin, F.-H., Náñez, J. E., Watanabe, T., & Sasaki, Y. (2013). Enhanced Spontaneous Oscillations in the Supplementary Motor Area Are Associated with Sleep-Dependent Offline Learning of Finger-Tapping Motor-Sequence Task. *The Journal of Neuroscience*, *33*(34), 13894-13902. https://doi.org/10.1523/jneurosci.1198-13.2013

Teo, J. (2009). Motor learning and neuroplasticity in humans. *Teo, J.T.H. (2009) Motor learning and neuroplasticity in humans. Doctoral thesis, UCL (University College London).*

Titone, S., Samogin, J., Peigneux, P., Swinnen, S., Mantini, D., & Albouy, G. (2022). Connectivity in Large-Scale Resting-State Brain Networks Is Related to Motor Learning: A High-Density EEG Study. *Brain Sci*, *12*(5). https://doi.org/10.3390/brainsci12050530

Ungerleider, L. G., Doyon, J., & Karni, A. (2002). Imaging brain plasticity during motor skill learning. *Neurobiol Learn Mem*, *78*(3), 553-564. https://doi.org/10.1006/nlme.2002.4091

Vaidya, C. J., Huger, M., Howard, D. V., & Howard Jr, J. H. (2007). Developmental differences in implicit learning of spatial context. *Neuropsychology*, *21*(4), 497-506. https://doi.org/10.1037/0894-4105.21.4.497

van Wijk, B. C. M., Beek, P. J., & Daffertshofer, A. (2012). Neural synchrony within the motor system: What have we learned so far? *Frontiers in Human Neuroscience*, *6*. https://doi.org/10.3389/fnhum.2012.00252

Verburgh, L., Scherder, E. J., Van Lange, P. A., & Oosterlaan, J. (2016). Do Elite and Amateur Soccer Players Outperform Non-Athletes on Neurocognitive Functioning? A Study Among 8-12 Year Old Children. *PLoS One*, *11*(12), e0165741. https://doi.org/10.1371/journal.pone.0165741

Voss, P., Thomas, M. E., Cisneros-Franco, J. M., & de Villers-Sidani, É. (2017). Dynamic Brains and the Changing Rules of Neuroplasticity: Implications for Learning and Recovery. *Front Psychol*, *8*, 1657. https://doi.org/10.3389/fpsyg.2017.01657

Weinstein, M., Myers, V., Green, D., Schertz, M., Shiran, S. I., Geva, R., Artzi, M., Gordon, A. M., Fattal-Valevski, A., & Ben Bashat, D. (2015). Brain Plasticity following Intensive Bimanual Therapy in Children with Hemiparesis: Preliminary Evidence. *Neural Plast*, *2015*, 798481. https://doi.org/10.1155/2015/798481

Wexler, E. M., & Stanton, P. K. (1993). Priming of homosynaptic long-term depression in hippocampus by previous synaptic activity. *Neuroreport: An International Journal for the Rapid Communication of Research in Neuroscience*, *4*(5), 591-594. https://doi.org/10.1097/00001756-199305000-00034

Winkler, I., Brandl, S., Horn, F., Waldburger, E., Allefeld, C., & Tangermann, M. (2014). Robust artifactual independent component classification for BCI practitioners. *Journal of Neural Engineering*, *11*(3), 035013. https://doi.org/10.1088/1741-2560/11/3/035013

Winkler, I., Haufe, S., & Tangermann, M. (2011). Automatic Classification of Artifactual ICA-Components for Artifact Removal in EEG Signals. *Behavioral and Brain Functions*, *7*(1), 30. https://doi.org/10.1186/1744-9081-7-30

Yang, Y., Chen, M., He, W., & Merrill, E. C. (2020). The Role of Working Memory in Implicit Memory: A Developmental Perspective. *Cognitive Development*, *55*, 100929. https://doi.org/https://doi.org/10.1016/j.cogdev.2020.100929

Appendix 1: Ethic Approval

The University of Waikato
Private Bag 3105
Hamilton, New Zealand, 3240
0800 WAIKATO (924 528)

HECS Human Ethics Committee
Brett Langley
Telephone +64 77 838 4060
Hecs-ethics@waikato.ac.nz

THE UNIVERSITY OF WAIKATO
Te Whare Wānanga o Waikato

14 December 2023

Nirol Bishnoi
Jadon Miller
Merel Hoskens
Rich Masters

Re: HECS Ethics Approval of Application HREC(HECS)2023#67 "A Fitter Approach for Convalescing Neuroplasticity: Implicit or Explicit Motor Learning Protocol"

Dear Nirol:

Thank you for submitting your amended application HREC(HECS)2023#67 for ethical approval.

We are pleased to provide formal approval for your project, including the following activities:

- Recruitment of up to 20 participants for an implicit or explicit learning motor learning study.
- Have participants complete two questionnaires that look at cognitive reinvestment and handedness.
- Fit participants with a neoprene electroencephalography (EEG) cap, which will measure brain activity from the main motor regions of your brain, including the frontal, and occipital regions (i.e. T7, Fz and Cz).
- Ask participants to learn new complex motor tasks using training instruments provided and complete a serial reaction time tasks over five lab sessions (30 to 60 minutes each). After the learning phase, ask participants to complete a test phase to determine the amount of motor skill learning and transfer.
- Brain activity will be measured with the EEG cap during all training and testing laboratory sessions.

Please contact the committee by email (hecs-ethics@waikato.ac.nz) if you wish to make changes to your project as it unfolds, quoting your application number with your future correspondence. Any minor changes or additions to the approved research activities can be handled outside the monthly application cycle.

We wish you all the best with your research.

Kind regards,

B Langley

Brett Langley, PhD
Chairperson
HECS Human Ethics Committee
University of Waikato

Appendix 2: Participant Information Form

Te Huataki Waiora - School of Health
The University of Waikato
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THE UNIVERSITY OF WAIKATO
Te Whare Wānanga o Waikato

Participant Information Sheet

Project name: Examining Neuroplasticity as a Function of Errors During Motor Learning

Investigators: Nirol (Master student), Jadon Miller, Dr Merel Hoskens, and Prof Rich Masters

Kia ora, my name is Nirol Bishnoi and I am currently doing a Master's degree at the University of Waikato. With Jadon Miller, a Summer Research Scholar, we would like to invite you to take part in our research project that seeks to find better approaches to enhancing neuroplasticity. Below is an information sheet about the study, your role, and importantly your rights, should you choose to be a participant. Please read this information carefully and feel free to ask any questions you might have.

Purpose of the study
Brain plasticity is used to describe the brain's ability to learn and the ability to develop new skills. The learning of new skill can occur implicitly or explicitly. With implicit learning is where there is a low conscious awareness on the movement during skill acquisition, whereas explicit motor learning involves high awareness on the movement. Implicit motor learning has been proven to be a more efficient way of skill learning, especially the skill is used under pressure situations. The purpose of this study is to determine whether implicit motor learning or explicit motor learning assists in better brain plasticity.

Procedures
You will be asked to arrive at the motor learning laboratory (TT0.10) at the University of Waikato, Te Huataki Waiora School of Health. Here, you will be asked to complete two basic questionnaires that look at cognitive reinvestment and handedness. You will then be fitted with a neoprene electroencephalography (EEG) cap, which will measure brain activity from the main motor regions of your brain, including the frontal, and occipital regions (i.e. T7, Fz and Cz). This is non-invasive and measures activity from the surface of your scalp. You will then be asked to learn a new complex motor task using training instruments provided and complete a serial reaction time task. This learning phase will occur over five short-termed lab sessions (30 to 60 minutes each), at the end of which, a test phase will be conducted to determine the amount of motor skill learning and transfer.

Potential risks or discomfort
The risk of this study is very minimal and unlikely to cause discomfort. You will be fitted with a neoprene EEG cap that has sensors in it to record your brain's activity. The electrodes will be against your scalp and we will use some gel to help them measure activity. This means that there might be some residual gel on your scalp after the study. Although the gel is entirely harmless and is easily wiped or washed off, it can cause mild irritation in some people with very sensitive skin. In our experience, this is unlikely to happen.

Confidentiality
Any personal data collected from you will be completely confidential. Your name or any identifying feature will not be associated with or represented in any research output. To protect

your identity, you will be given a study ID code that will be used with the collection of any research data so no one can trace the data back to you.

Study Withdrawal
Your participation is entirely voluntary and you have the right to not answer any question or do any activity don't you want to do. You also have the right to withdraw from the study at any time. After you complete the study, you have an additional week in which you are free to withdraw and have any data you have contributed removed. To withdraw, you just need to let me or any one of the research team know. You do not need to provide a reason for withdrawal and we will not ask you for one.

Outcomes:
The data obtained from this study will contribute to a Master's thesis. It will also contribute to a University of Waikato Summer Scholarship poster presentation. Furthermore, we expect that this study might also result in a Journal manuscript or Conference presentation. We would also like to send you a study report at the end of this study – please indicate on the consent form whether or not you would like to receive this. All data for this study will be stored on a University of Waikato encrypted and secure server that is only accessible by the research team. As per University policy, this will be retained for five years, after which it will be permanently deleted.

Other issues, questions or concerns
If you have any questions or concerns about the research, please feel free to contact: Nirol (email: nirolbishnoi1029@gmail.com), Merel Hoskens (email: mhoskens@waikato.ac.nz, telephone 027 8260535) or professor Rich Masters (email: rmasters@waikato.ac.nz, telephone 838 45 00 or ext. 6206).

This research project has been approved by the Human Research Ethics Committee of the University of Waikato under HREC(HECS)2023#67. For any ethical questions or concerns please contact the Chair of the Committee, email hecs-ethics@waikato.ac.nz, postal address, University of Waikato, Te Whare Wananga o Waikato, Private Bag 3105, Hamilton 3240.

Appendix 3: Consent Form

Te Huataki Waiora - School of Health
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THE UNIVERSITY OF WAIKATO
Te Whare Wānanga o Waikato

Consent form

Project Title: Examining Neuroplasticity as a Function of Errors During Motor Learning

Investigators: Nirol (Master student), Jadon Miller, Dr Merel Hoskens, and Prof Rich Masters

I _____ voluntarily consent my participation in the above research study at the University of Waikato under the guidance of _____. I have had the opportunities to ask any questions I had related to the study, and I am completely satisfied by the explanations provided by_____.

- I have been supplied with and read the study Participant Information Sheet that includes thorough information on the study, including the purpose, activities, risks and my rights as a participant.
- I understand that the study data will be used in a Masters thesis, presentations, and might be part of scientific publications.
- I have the right to refuse to answer or do any activity, as well as withdraw from the project at any time until one week after participation and do not have to provide a reason.
- I am aware that all the information collected will be unidentified via coding to ensure my privacy protection while reporting or publishing of the research.
- I am participating in this project of my own volition and I have not been coerced in any way to participate.

o I would like to be given a summary of findings from the study when it is concluded.

Signature of Participant: _____
Date: ____/____/____

I, the undersigned, was present when the study was explained to the subject/s in detail and to the best of my knowledge and belief it was understood.

Signature of Researcher: _____
Date: ___/____/____

Contact Details for Researchers: If you have any questions or concerns about the research, please feel free to contact: Nirol (email: nirolbishnoi1029@gmail.com, telephone: 02041493383), Merel Hoskens (email: mhoskens@waikato.ac.nz, telephone: 027 8260535) or professor Rich Masters (email: rmasters@waikato.ac.nz, telephone 838 45 00 or ext. 6206).

Appendix 4: Participant Demographics

Participant Demographics

Participant No. _____

First Name:	
Family Name:	
Date of Birth:	Age:
Gender (circle) :	Male / Female
Handedness (circle):	right hander / left hander

Appendix 5: Measurement Scales

5.1. The Movement Specific Reinvestment Scale

THE MOVEMENT SPECIFIC REINVESTMENT SCALE
© Masters, Eves & Maxwell (2005)

Participant No. _____ Date: _____

DIRECTIONS: Below are a number of statements about your movements in general. Circle the answer that <u>best</u> describes how you feel for each question.

1	**I remember the times when my movements have failed me.**					
	strongly disagree	moderately disagree	weakly disagree	weakly agree	moderately agree	strongly agree
2	**If I see my reflection in a shop window, I will examine my movements.**					
	strongly disagree	moderately disagree	weakly disagree	weakly agree	moderately agree	strongly agree
3	**I reflect about my movement a lot.**					
	strongly disagree	moderately disagree	weakly disagree	weakly agree	moderately agree	strongly agree
4	**I try to think about my movements when I carry them out.**					
	strongly disagree	moderately disagree	weakly disagree	weakly agree	moderately agree	strongly agree
5	**I am self-conscious about the way I look when I am moving.**					
	strongly disagree	moderately disagree	weakly disagree	weakly agree	moderately agree	strongly agree
6	**I sometimes have the feeling that I am watching myself move.**					
	strongly disagree	moderately disagree	weakly disagree	weakly agree	moderately agree	strongly agree
7	**I am aware of the way my body works when I am carrying out a movement.**					
	strongly disagree	moderately disagree	weakly disagree	weakly agree	moderately agree	strongly agree
8	**I am concerned about my style of moving.**					
	strongly disagree	moderately disagree	weakly disagree	weakly agree	moderately agree	strongly agree
9	**I try to figure out why my actions failed.**					
	strongly disagree	moderately disagree	weakly disagree	weakly agree	moderately agree	strongly agree
10	**I am concerned about what people think about me when I am moving.**					
	strongly disagree	moderately disagree	weakly disagree	weakly agree	moderately agree	strongly agree

5.2. Adaptive Movement Specific Reinvestment Scale

THE MOVEMENT SPECIFIC REINVESTMENT SCALE (adaptive version).
© Masters, Eves & Maxwell (2005)

Directions: Think back on the shuffleboard task you performed today, and please answer the following questions:

Participant No. _____ Date _____

1. **I remember the times when my shuffleboard movements had failed me.**

   strongly disagree | moderately disagree | weakly disagree | weakly agree | moderately agree | strongly agree

2. **I reflected about my shuffleboard movement a lot.**

   strongly disagree | moderately disagree | weakly disagree | weakly agree | moderately agree | strongly agree

3. **I tried to think about my shuffleboard movements when I carried them out.**

   strongly disagree | moderately disagree | weakly disagree | weakly agree | moderately agree | strongly agree

4. **I was aware of the way my body works when I carried out the shufflebaord movement.**

   strongly disagree | moderately disagree | weakly disagree | weakly agree | moderately agree | strongly agree

5. **I tried to figure out why my actions failed.**

   strongly disagree | moderately disagree | weakly disagree | weakly agree | moderately agree | strongly agree