Motor Learning

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Introduction

Motor learning involves processes that develop with experience, which changes an individual's behaviours and internal state. These processes are evidenced by "…relatively permanent improvements in the potential or capability for skilled behaviour" (Schmidt & Lee, 2011, p.327). Examples of processes or internal states that change with learning are: attention, memory, perception and neuromuscular patterns of activation. Although developmental influences, such as a learner's physical and cognitive maturation, will affect an individual's capability for skilled behaviour, motor learning is specifically defined with respect to changes that occur as a consequence of experience or dedication to practice. Other terms that also refer to the phenomenon of motor learning are: motor skill acquisition, perceptual-motor learning, psychomotor learning, and sensorimotor learning.

Effective practice for motor learning tends to be goal-oriented and may be as few or as many trials as demanded by the complexity of the task and the corresponding skill of the learner. Improvement in an individual's capability for skilled movement may consist of a change in quality of movement production (such as increased motor efficiency leading to decreased energy expenditure, faster reaction time, and greater force production) and/ or a greater likelihood of success in achieving desired outcome goals, such as improvement in response consistency or a reduction in error. Researchers are often concerned with determining how these variables relating to learning efficiency and effectiveness can be improved through manipulations to information and conditions of practice; such as instructions, feedback and task scheduling.

Though learning is best indexed by changes in behavioural outcomes, the processes and internal states influencing an individual's current performance are not necessarily related to learning. For instance, fatigue after a long practice session may result in markedly diminished performance, or the presence of a monetary incentive could spur an individual to an elevated, but atypical level of performance. Thus, immediate conclusions made on the efficacy of a practice intervention could be masked by these temporary performance factors. Hence researchers control for the impact of such performance factors on assessments of learning by measuring performance on a retention or transfer test, typically administered after a period of delay known as the retention interval (see Sections 4.1-4.2 for further discussion). The "gold standard" for the retention interval that motor learning researchers apply is ~24 hours, but others have measured performance for longer periods in order to make conclusions about stable changes in performance and the degree of forgetting.

Learning is also possible without any overt changes in performance. Sometimes this is referred to as “overlearning” (Schmidt & Lee, 2011), which manifests as a period of performance plateau or saturation during practice. While there are no indicators of behavioural change, changes are occurring in the processes underpinning motor control. As an illustration, attentional processes tend to shift from more “controlled” to more “automatic” (i.e., from attentionally-demanding to not demanding) with increased skill (Fitts & Posner, 1967). While there may not be an overt change in performance, as skill execution becomes more autonomous, an individual is better able to simultaneously perform a secondary, attentionally-demanding task without interference (see Section 3.1). A lack of change in performance may also signal a failure to measure appropriate aspects of performance or use a sensitive enough measure (such as moving from looking at outcomes to movement form or from number of target hits to millimetre differences in target accuracy).

Primary theories, frameworks and associated concepts

We discuss four general theoretical approaches which are most frequently cited in motor learning research. These comprise: 1) cognitive/ information-processing, 2) ecological dynamics, 3) neurophysiological models and mechanisms, and 4) psycho-social perspectives. These approaches reflect differential emphasis on internal “representational” processes (information processing) versus non-representational, behavioural dynamics’ approaches (ecological dynamics), as well as different levels of analysis (neurophysiological) versus behavioural. They also result from differences in methods and experimental tasks, which we expand upon below (e.g., discrete actions versus continuous actions).

Cognitive / information-processing

Cognitive information-processing accounts share similarities in that these approaches to motor learning are heavily influenced by determination of the cognitive processes which mediate performance and learning. Error processing and feedback are important facets of these theories and frameworks detailed below.

Adam's closed-loop theory

Adam's closed-loop theory emphasizes the importance of processing information related to movement outcomes (or knowledge of results) and sensory feedback for motor learning (Adams, 1971). Two traces or states of memory are thought to guide movement. The memory trace provides the motor commands to drive the initial portion of a movement, while the perceptual trace provides a "reference of correctness". This latter memory state is important for the detection of discrepancies between sensory feedback and an intended movement, affording what is termed "closed loop" (feedback-based) control until movement completion. Experience strengthens these memory traces.

In initial learning, when an individual does not have correct experiences of a motor skill, the perceptual trace of the correct movement would be weak as there are relatively few correct movement traces compared to incorrect traces. The learner is heavily dependent on outcome-related feedback, typically provided by external sources, to help guide any repetitions if the task goal was not achieved. As the performer improves with practice, the perceptual trace for the correct movement increases in strength, as a relatively large number of correct perceptual traces are accumulated compared to incorrect ones. Dependence on external feedback diminishes as the correct perceptual trace is strengthened and proficiency increases.

One of the long-lasting legacies of this theory is the importance placed on various types of feedback for minimizing error and guiding performers towards increasing accuracy. With practice, there is an increased reliance on response-produced sensory/ intrinsic feedback rather than externally provided/ augmented feedback. This theory prompted much research into the role of feedback for motor learning and the importance of the development of error-detection mechanisms for effective motor performance. Although the theory is still widely cited in many text-books, it is rarely cited in current motor learning research.

Schema theory

Schema theory was developed by Richard Schmidt, a student of Adams (Schmidt, 1975). The main difference between this theory and that of Adam's is that in schema theory, the movement can be controlled by the motor trace (or motor program) and executed without influence from sensory feedback (termed "open-loop" control). As such, the motor program contains motor commands which are specified in advance of the movement. This idea of a motor program was not, however, unique to schema theory (e.g., Keele, 1968). As with Adam's theory, there are two memory states: 1) the recall memory/ schema, which controls movement execution, and 2) the recognition memory/schema, which provides a reference of correctness for comparing sensory feedback, allowing for error evaluation at the end of the movement or after the motor program has run. Similar to closed-loop theory, feedback is essential for motor learning in schema theory, as knowledge of movement outcomes is necessary for developing the recall and recognition schemas.

A key aspect of schema theory for motor learning is the idea that individuals acquire "generalized" motor programs (what are often referred to as "GMPs"). Rather than specific programs for every action, the idea was that individuals develop and store abstract representations for a class of motor skills which contain "invariant" features (e.g., the proportion of time between onset and offset of muscles, which stay relatively consistent despite changes to the effectors used or the overall duration of an action). With practice, relations are developed between specific parameters (i.e., overall timing, overall force, the limb or muscles used) as well as contextual factors and various outcomes or sensory consequences. These relations are referred to as schemas. For instance, to pitch a baseball to a catcher, a pitcher would have stored a template of a pitch which would contain relatively invariant features. Taking into account the desired outcome (e.g., a 60 ft pitch) and contextual conditions, they would specify the effector (e.g., dominant right arm) and the absolute force (e.g., 15 N) that would be needed to cover the desired distance. Even if the pitcher had not pitched that distance before, if they had pitched to similar distances, they would be able to use the stored schema to select parameters which would likely produce the novel action. Hence, schema theory provides an explanation for how individuals are able to execute novel variations of a motor task with unexpected proficiency.

In contrast to closed-loop theory, errors during practice are not detrimental for learning as they provide information which informs the schema. Considerable empirical evidence exists supporting this idea through what is known as variability of practice research (van Rossum, 1990). More variable practice around a criterion task tends to lead to poorer immediate performance than constant practice of the same task, but importantly results in more robust long-term learning and transfer to new, unpractised conditions (e.g., Shea & Kohl, 1991). Variation in task parameters strengthens the recall and recognition schemas for a motor skill such that with increased movement experiences, not only is execution accuracy increased via the recall schema (i.e., correct selection of parameters), but the recognition schema gives a more accurate prediction of anticipated sensory effects, improving fast, feedforward-based error detection. As stated below, these ideas concerning feedforward and feedback based error correction strategies are central to computational theories of motor control and the idea of internal models, which have tended to dominate laboratory-based research into motor learning processes over the past decade.

Internal models

Motor learning entails the mastery of sensorimotor transformations or mappings relating motor commands to sensory feedback. Computational neuroscientists and engineers have made significant progress in studying and modeling how these transformations are learned through the concept of internal models (e.g., Wolpert, Ghahramani & Jordan, 1995; Wolpert, Miall & Kawato, 1998). Major overlaps exist between the functions of internal models and memory representations based on schema theory. Two types of internal models have been conceptualized. Analogous to the concept of recognition memory in schema theory, the forward model captures the causal relationship between inputs (motor commands) and outputs (sensory consequences) of the motor system in a given context. The function of the inverse model is similar to recall memory in that it inverts the causal relationship between sensory consequences to motor commands to provide an estimation of the motor commands for generating a desired outcome.

To acquire and maintain reliable internal models for motor control, an individual learns to associate repeated pairings of motor commands with the corresponding sensory consequences. For learning or behavioural adaptations to take place and for these internal models to be updated, the learner must experience a discrepancy between the expected and actual sensory consequences as a result of movement execution. Hypothetically, a copy of the motor command is generated, termed an "efference copy", which interacts with the forward model to give a prediction of the sensory consequences of an action (i.e., feedforward processing). When discrepancies are experienced, both the forward and inverse internal models are updated, so that motor commands are essentially modified to suit the new sensorimotor mapping. It has been suggested that the forward model is updated before the inverse model and plays a role in the training of the inverse model.

Empirical work on internal models is typically based on what are termed visuomotor or dynamical (force-field) adaptation tasks. In adaptation studies, perturbations are introduced so that a sensory discrepancy is experienced, requiring modifications to motor commands. With sufficient practice, learners adapt to the perturbation and error is reduced (e.g., aiming to targets which are inverted or rotated). Upon removal of these perturbations, "after-effects" are noted, which are compensatory actions opposite to the direction of the perturbation. These after-effects arise even when performers are informed that the environment is normal and hence are unintentional (or implicit). They are taken as evidence that a performer's internal models or sensorimotor mappings for the task have been updated and hence some learning has occurred. Recent debates in this area are often centred around the neurophysiological mechanisms underpinning the various models and the independence of error signals which drive implicit updating and explicit /strategic changes to motor plans (e.g., Huang & Shadmehr, 2007; Taylor & Ivry, 2014).

Cognitive effort and challenge

Motor learning is not merely influenced by the amount of practice, but also by the quality of the practice. Two well studied practice conditions are often cited in support of practice quality effects on motor learning; the contextual interference effect (Shea & Morgan, 1979), related to practice organization of multiple skills and the guidance hypothesis (Winstein & Schmidt, 1990), related to the impact of augmented feedback on motor learning.

An interference that occurs when a motor skill is practised in the context of other skills is termed the contextual interference (CI) effect. This interference is actually good for longer-term learning, but not for short-term performance. When practice is organized in a more random manner, by interleaving the practice trials of all skills so that each skill is typically not repeated more than once, overall performance is degraded in comparison to blocking practice. In blocked practice, trials of one skill are performed repetitively before switching to practice on the next skill, such that CI is low. However, on retention or transfer tests, an “acquisition-retention reversal” is typically observed, where the presence of greater interference in the practice context (random practice) results in long lasting learning benefits compared to low interference blocked practice. These CI effects are thought to be due to differences in cognitive-processing activities. Random practice promotes deeper processing and understanding of each skill (“elaborative processing hypothesis”; Shea & Zimny, 1983) or/and increased cognitive effort in organizing plans of actions during practice (“forgetting and reconstruction hypothesis”; Lee & Magill, 1983) compared to blocked practice. In general, conditions that make practice more challenging or effortful are more beneficial to motor learning.

Research on the guidance hypothesis underscores the importance of practice quality, related to cognitive processing, on motor learning. The guidance hypothesis arose out of research related to the frequency and timing of augmented (also termed extrinsic) feedback, particularly information related to the outcome of the movement, termed knowledge of results (KR). Augmented feedback, which can be provided by a coach or teacher, or perhaps by some technical device such as a phone video app, serves to guide the learner through the immediate highlighting of errors in performance. However, when provided too soon or too frequently, augmented feedback can be detrimental to learning, eliciting an acquisition-retention reversal as discussed for the CI effect. So for example, more frequent KR (e.g., KR provided on 100% of trials) is detrimental to learning relative to less frequent KR (e.g., Sullivan, Kantak & Burtner, 2008).

According to the guidance hypothesis, the prescriptive aspect of KR prevents individuals from processing their own intrinsic feedback, thus impairing error detection and correction processes. The result is that learners become dependent on the extrinsic KR feedback and are unable to apply appropriate adjustments or corrective strategies when this source of feedback is unavailable. Withholding or delaying KR or providing summary feedback only after several trials serves to reduce the guidance effects of KR on motor learning (Schmidt & Lee, 2011). When participants have been asked to estimate their error on each trial before receiving KR on 100 % of the trials, this strategy has also been effective in reducing the negative retention effects of practising with a high frequency of KR (e.g., Guadagnoli & Kohl, 2001). Here, engaging in effortful activities related to detection of error benefited learning.

The principle common to both contextual interference and the guidance hypothesis of augmented feedback is that effortful or challenging practice benefits learning while potentially suppressing practice performance. Yet, there are documented cases where too much challenge was found to be a hindrance to learning. For instance, when random and blocked practices were separately administered to two groups of novices that were learning a nominally (or inherently) difficult task, longer-term learning in the random practice group was diminished compared to the blocked practice group (Guadagnoli, Holcomb & Weber, 1999). It was argued that task and individual factors moderated the gains that could be attained from incorporating challenge into practice. Guadagnoli and Lee (2004) proposed the challenge point framework to help explain how challenge and learning interact. A moderate degree of practice challenge or what they term "functional task difficulty" is optimal for learning. Functional task difficulty is a measure of difficulty that accounts for the interaction of nominal task difficulty and a performer's skill level. According to the challenge point framework, practising at a functional task difficulty level too low or too high for an individual is sub-optimal for learning. The challenge point framework nicely illustrates the relation between short-term performance in practice and longer-term learning. Performing at a more challenging level in practice, which would result in poorer short-term performance, should lead to more gains in terms of learning and improvement than that associated with low challenge and low error practice.

Ecological dynamics

A departure from the cognitive perspectives discussed thus far, and borrowing key ideas from ecological psychology and complex dynamical systems to theorize about human motor learning, an ecological dynamics approach to understanding learning processes was developed (also referred to as a constraints-led approach; e.g., Davids, Button & Bennett, 2008; Kelso, 1994; Kugler & Turvey, 1988; Newell, 1986). The ecological dynamics approach was established on the notion of self-organization in biological systems, where adaptive movement behaviours emerge from continuous interactions between individuals, their task, and the environment in which they perform. An example of self-organization can be seen in gait transition as speed of locomotion is increased in a walking individual. As speed (the control parameter) increases, the relative timing and step characteristics (order parameters) are spontaneously re-organized to transition from walking gait to jogging gait. Self-organization is also seen in coordination dynamics research involving bimanual inter-limb movements. Decoupling the limbs to perform relative phase patterns other than in-phase (symmetrical flexion/extension of both limbs, 0° phasing) or anti-phase (alternating flexion/extension, 180° phasing), which are termed intrinsic attractors, is difficult and produces instability. With increasing movement velocity, that is, a change in some control parameter, the dynamical system will transition back to a more stable attractor state (Haken, Kelso & Bunz, 1985). Hence, learning is conceptualized as a change in the attractor landscape and one of self-organization and stability/instability transitions. Where previous, more cognitive based theories have been good at describing and explaining discrete actions or sequences of action (with clearly defined beginning and end points), continuous actions have been well described through an ecological dynamics approach.

Behavioural outcomes in such self-organizing systems are considered to be mostly independent of high-level executive input and are governed by structural (body-related) and informational (visually-related) constraints. Movement "patterns" that emerge are a result of perception-action coupling, wherein perceptual information guides or regulates action directly, independent of any type of preplanned motor program. A fundamental feature of the ecological dynamics approach to motor learning is that there is inherent neurobiological "degeneracy" in the perceptual and action systems (Edelman & Galley, 2001). This means that multiple functionally equivalent ways of attaining the same outcome goals can be generated through various biomechanical configurations of the physical body. Degeneracy is illustrated in the different types of passes a Frisbee player could make (e.g., forehand, backhand, hammer throw) and biomechanical variations in which these passes may be executed that would achieve the same performance outcome of hitting a target. A Russian scientist, named Nikolai Bernstein, was one of the first researchers to consider the influence of context and fluctuations in the internal and external factors impacting skill performance (Bernstein, 1996). He posited that the same motor commands would not achieve identical outcomes from one trial to another, as the internal states vary in an individual from trial to trial due to inherent noise in the motor system. The same could be said for the variability in the performance context. Accordingly, it is the process of solving variations of motor problems that prepare a learner to adapt to ever-changing interactions in constraints. Bernstein advocated for variability in practice that encourages exploration of motor solutions that achieve the same task objective, rather than mere repetitive practice of a single motor solution. This guideline for structuring practice is especially applicable to acquisition of “open skills” (see first paragraph of the Psycho-social perspectives).

A constraint-led framework is often adopted to promote motor learning under the ecological dynamics approach. Imposing various task (e.g., equipment or rule adaptation) and/or environmental constraints (e.g., weather, playing surface), given the individual constraints (e.g., age, skill level), can direct learners to “specifying information” (i.e., relevant information for regulating a movement) and “affordances” (i.e., movement possibilities). A constraints-led coaching or instructional design is founded on ecological dynamics principles and the idea that behaviours emerge as a consequence of manipulation to constraints rather than as a result of a specific aim to produce one type of motor pattern or solution (Davids et al., 2008). Whilst there is considerable evidence that constraints can change behaviours in the absence of specific intentions to change, there is less evidence that this way of instructing, where movements are brought about through a discovery and constraints heavy environment is better for performance and learning than a more prescriptive approach where learners are directed to a particular motor solution. Importantly, both an information processing and constraints-led approach to behaviour change would encourage active effort on the part of the learner, with practice environments that are designed to maximize the match between conditions encountered in test or competition.

Neurophysiological models and mechanisms

With advancements in technology and increased accessibility to brain imaging and neurophysiological tools, researchers have begun to detail the neural processes and circuitry involved in motor learning (e.g., Seidler, 2010). These neural processes have been detailed in relation to memory consolidation (e.g., Shadmehr & Holcomb, 1997), that is, the offline processes that take place outside of practice, which serve to make short-term memories more long-term. As well, these processes have been detailed with respect to different forms of learning such as use-dependent, error-based, and reinforcement learning (e.g., Huang, Haith, Mazonni & Krakauer, 2011).

Neurophysiological work on use-dependent (also known as Hebbian) learning has shown that movement repetition induces short-term neural plasticity (e.g., Classen, Liepert, Wise, Hallett & Cohen, 1998). In Hebbian learning, when a neuron fires and elicits activity in another, or when a stimulus elicits a certain pattern of neural activity, the synaptic connections between these neurons strengthen (a cellular process known as long-term potentiation, LTP). This strengthening means that the stimulus will tend to elicit the same neural activity on subsequent occasions. The reverse, that is a lack of/no association between neural activity and synaptic connections result in long-term depression (LTD), a weakening in the strength of synaptic transmissions. Repeated elicitations of such synaptic connections are strengthened irrespective of feedback regarding error or outcome efficacy in Hebbian learning. Hebbian learning is underpinned by neural plasticity within and between areas of the cerebral cortex, including the primary motor and somatosensory cortices (Buonomano & Merzenich, 1998; Classen et al., 1998). In supervised or error-based learning, feedback is pertinent for error correction and adaptation to a changing environment (Seidler, Kwak, Fling & Bernard, 2013). Augmented or intrinsic sensory feedback, containing information on magnitude and direction of error, is used to update subsequent motor commands and predictions of sensory consequences. Error-based learning is thought to be driven by neural plasticity (particularly LTD) in the cerebellum, which is based on sensory prediction errors (e.g., Diedrichsen, Hashambhoy, Rane & Shadmehr, 2005; Ito, Yamaguchi, Nagao & Yamazaki, 2014).

A reinforcement learning mechanism is also thought to be involved in learning from errors, involving the midbrain dopamine system, anterior cingulate cortex (ACC), basal ganglia, and other higher brain-level cortical areas. When consequences of a response are worse than predicted, a negative dopaminergic signal (i.e., decrease in dopaminergic neuronal firing) is elicited and projected to various cortical structures. This dopamine signal reaches the ACC and results in neural disinhibition, which can be seen by EEG (electroencephalography) measures of Error Related Negativity (ERN) in frontal/central regions of the brain (Holroyd & Coles, 2002). When consequences are better than predicted, the dopamine signal is reversed. Dopaminergic neurons in other cortical regions also show phasic activations corresponding to rewards and reward-predicting stimuli that appear to be crucial for reinforcement learning (as well as memory consolidation, see next paragraph; McGaugh, 2000; Wadden, Borich & Boyd, 2012). At the cellular level, dopamine influences synaptic plasticity via LTP and LTD. Notably, when dopaminergic projections to the primary motor cortex were blocked (through surgical lesions) in rodents, new skill learning was reducedd while existing skills were not impacted (Hosp, Pekanovic, Rioult-Pedotti & Luft, 2011).

Memory consolidation processes are also linked to neurobiological evidence alluding to the importance of dopamine for learning. These consolidation processes are subsumed within the definition of motor learning. Consolidation refers to offline neurobiological processes that serve to stabilize or enhance memory, whereas motor learning is the relatively permanent improvement in capacity for skilled movement that is due to both online (during practice) and offline processes, that happen at all levels of the sensory-motor system. During memory consolidation, neurophysiological processes influence a memory trace in two distinct time frames (Karni et al., 1998). The fast (synaptic) consolidation involves synaptic protein synthesis and strengthening of synaptic transmissions that are active during skill performance. The slow (systems) consolidation, which can last for weeks, involves reorganization of neural networks. Memories, which were encoded and dependent on the hippocampus for retrieval, are relieved of this dependency and moved to the neocortical system for long-term storage through this slow system. Both types of consolidation are necessary to induce permanent changes to memory and motor skills.

Events that happen during practice and post-practice can impact memory consolidation, serving to augment and facilitate or negatively impact and interfere. For example, immediate practice of a counter-rotation after first adapting to an opposite visuomotor rotation (a virtual environment whereby visual feedback representing hand movement is rotated in relation to actual hand movement) usually induces (retroactive) interference resulting in significant reduction in retention of the first rotation (see discussion on visuomotor adaptation in final paragraph of “internal models” discussed above and “transfer” in the final sections below). In a task involving fast rhythmic finger movements, a non-invasive electromagnetic procedure that interferes with local brain function, known as repetitive Transcranial Magnetic Stimulation (rTMS), disrupted memory consolidation when applied to the primary motor cortex immediately after practice (Muellbacher et al., 2002). A lack of sufficient sleep or rest after skill practice has also been shown to interfere with consolidation processes. For example, when learners were sleep-deprived on the first night after a practice session, they showed less pronounced offline improvement in a motor sequence task at a 48-hour delayed retention test, compared to learners who had two regular nights of sleep after practice (Fischer, Hallschmid, Elsner & Born, 2002).

Psycho-social models

The psychological construct of motivation, defined as the direction, intensity and persistence of effort in certain behaviours (Vallerand & Thill, 1993 as cited in Crocker, 2007), has received renewed attention as a potential motor learning mechanism. Motivation is thought to influence motor learning based on processes related to competence, social-relatedness and autonomy (Deci & Ryan, 2000). Although motivation has always been regarded as important in exerting temporary energizing effects on performance and the quality or amount of practice, researchers have accumulated evidence supporting the idea that motivation-related processes have a direct impact on motor learning. This has led Wulf and Lewthwaite (2016) to propose the OPTIMAL (Optimizing Performance Through Intrinsic Motivation and Attention for Learning) model. The OPTIMAL model groups together learning related effects that are thought to be driven through the satisfaction of basic psychological needs of competence and autonomy coupled with an externally-related attentional focus. Practice interventions that enhance expectancies in performers (e.g., self-efficacy, perceived competency, or success expectations) and perceived autonomy (a sense of agency and control) have benefited motor learning.

The authors of the OPTIMAL model propose that meeting the basic psychological needs of competence and autonomy increases energy expenditure, cognitive effort, and positive affect, which exerts a positive impact on motor performance and learning. Elevated competency perceptions and autonomy also tend to be associated with other cognitive and attentional states that have enhanced performance and learning, such as improved goal setting, concentration, adoption of an external focus of attention, or lowered debilitating concerns about one’s lack of ability. Neurobiochemical processes related to consolidation and dopamine release have also been used to explain how motivation might directly impact motor learning. Although the OPTIMAL model is based on empirical evidence and combines a variety of potential effects and mechanisms into an integrated model, it is relatively new and awaits verification. Because of it’s a rather all-encompassing framework, it is difficult to refute the model, but there has been evidence that serves to question the moderating role of motivation in learning effects (e.g., Carter, Smith & Ste-Marie, 2016; Ong, Lohse & Hodges, 2015). On the positive side, this model has led to a greater appreciation of psycho-social influences on mechanisms of motor control and learning, which until now had mostly been at best controlled or at worst, discounted or ignored.

Learning Phases and Stages

Researchers and practitioners have noted certain patterns and characteristics of performance as motor skills are acquired, which has led to various conceptualizations about phases or stages that describe learning and the progression through skill levels (from novice/beginner to expert). While these stages are sometimes described as discrete and separated in such a way as to appear independent, most researchers acknowledge that skill progressions are likely blended and continuous in nature. Moreover, there is consensus that there is considerable variation between individuals with respect to how they learn. In this way, phases represent general observations about processes likely to be operating at a specific point in time, rather than being predictive of how people will learn when looking across different time scales. Below we consider two primary ways skill progressions have been considered, which we have broadly divided into progressions based on higher level cognitive processes and progressions based on lower-level motor system reorganization. However, we also acknowledge that these phases have also been considered on a computational level (e.g., in terms of fast and slow processes) at a brain systems level (e.g., in relation to progressions from cortical to cerebellar brain structures) as well as at a cellular level (related to potentiation of neurons and synaptic connections), which we do not discuss here.

Progressions in learning based on a reduction or change in higher-level, cognitive processes

Several theorists have proposed that acquisition of motor skills begins in a cognitively demanding ("cognitive") stage (e.g., Fitts & Posner, 1967). In this stage, performance is initially characterized by large errors and inconsistency. Working memory and attentional resources are heavily tapped during this early stage of learning, referred to as "controlled processing" (Schneider & Shiffrin, 1977). Novice performers are thought to consciously control skill execution, attending to how the skill is performed and the mechanics of the action. Declarative knowledge (i.e., facts, rules and strategies) on "what to do" (or what not to do) is accumulated in the cognitive stage (e.g., Anderson, 1982). If learners are overloaded with a second task to perform, a decrement in performance (or interference) is likely to be observed on either or both tasks. In this stage, performance tends to improve quickly (i.e., exponentially – or what has been referred to as the power-law of practice; Crossman, 1959; Newell & Rosenbloom, 1981) and consistency in outcome attainment and movement production typically improves in concert with overall accuracy. People have referred to graphs illustrating acquisition rate over time, with respect to some measure of performance, as performance or learning curves (Schmidt & Lee, 2011). These can be at an individual or group (mean) level. The rate of acquisition is aided by such methods as instructions, error feedback, appropriate task-constraints and observational learning, which enable the performer to generate an adequate movement solution and get the movement "in the ballpark".

Subsequent to the cognitive stage, performance continues to improve with practice, although the gains are usually gradual past the initial stage of learning. This intermediate, "fixation" stage (Fitts & Posner, 1967) may consist of periods of trial and error or discovery of motor solutions, in which skill execution is likely to mostly be defined by controlled processing. As performances become more consistent and biomechanically-efficient, movement production becomes more autonomous. Hence the final stage of learning is aptly named the "autonomous" stage (Fitts & Posner, 1967). Here, performance error is low and outcome consistency high. Instead of relying on declarative knowledge, learners have proceduralized their knowledge on "how to" perform the task, such that it is less accessible to conscious awareness and hence less verbalizable. Skill execution occurs with automaticity or "automatic processing", meaning little cognitive effort or attention is required for the skill to be performed well. With automatic processing, a performer is able to perform a second task with little to no interference. There are many sport-related empirical studies showing that expert performers (e.g., in golf) are able to perform just as well in a single-task condition (e.g., putting only) as under second-task conditions (additional performing a listening word search task; e.g., Beilock & Carr, 2001). Given that such findings define skilled but not novice performers, suggests that with advancing skill, a level of automaticity in the primary task allows resources to be allocated to other tasks (such as monitoring other players or reading the lay of the ground in putting).

At the autonomous stage, performance can be negatively impacted by an inward shift towards the self, known as "self-focused attention", or skill-focused attention, which is a shift towards use of declarative knowledge and step-by-step conscious processing of skills (e.g., Gray, 2004; Wulf, 2013). Other concepts similar to the skill-focused attention are the “explicit monitoring hypothesis” (e,g., Beilock & Carr, 2001), “constrained action hypothesis” (e.g., Wulf, McNevin & Shea, 2001), and the “reinvestment hypothesis” (e.g., Masters & Maxwell, 2004). The principle central to these accounts is a hypothesized regression towards an early cognitive control stage and monitoring of skill that interferes with automaticity and effectiveness of skill execution. In high-stake contests, this regression leads to performance akin to “choking”, the term that describes uncharacteristic performance decrements for an individual performing under pressure conditions. In accordance with the reinvestment hypothesis, experienced performers would be more likely to “choke” under stressful or attention-demanding situations if they accumulated a wealth of declarative knowledge early in learning (i.e., in the cognitive stage). This propensity for reinvestment is not only dependent on how skills were acquired and the amount of declarative knowledge, but also on characteristics of the individual and their propensity to reinvest (Masters, Polman & Hammond, 1993).

Although there is significant evidence that motor learning of novel skills is typically defined by explicit, declarative processes related to how to perform, this way of learning is not necessarily ubiquitous for all skills, nor is it necessarily the best way of learning. We can learn to kick or throw a ball, or jump without explicit knowledge as to how we are performing these skills. To learn implicitly refers to acquisition of a skill without conscious awareness of the products of learning or regularities that govern performance success. In other words, implicit motor learning bypasses the accumulation of declarative knowledge while procedural knowledge is acquired (e.g., Masters & Maxwell, 2004). In contrast, explicit motor learning normally follows guided or prescriptive learning environments, whereby learners become consciously aware of knowledge (e.g., task-structure, strategies) relevant to the skill they have acquired. Patients with amnesia who acquire new motor skills provide evidence for this implicit mode of learning, as while these patients have clearly acquired procedural knowledge to perform the tasks, they can neither recollect the learning experience nor verbally report explicit knowledge relevant to the skill (Nissen, Willingham & Hartmann, 1989). There is some empirical evidence that practice methods which are more implicit in nature, such as progressing through practice environments where errors are minimized (e.g., easy to difficult) or providing instructions that promote an external focus of attention, are effective for preventing performance decrements when participants later are tested under high stress or high task demands that exceed attentional capacity (e.g., Maxwell, Master, Kerr & Weedon, 2001; Ong, Bowcock & Hodges, 2010; Wulf 2013). By learning implicitly, learners avoid accumulating declarative or explicit knowledge of a skill and hence do not reinvest or revert to a conscious mode of control under pressure which could hamper performance.

Learning progressions based on lower-level, motor-system adaptations

The idea of spontaneous neural reorganization (i.e., self-organization) as a result of experience is central to ideas about motor behaviour being an emergent property of various internal and external constraints. Consistent with what is now termed the ecological-dynamics perspective (Davids et al., 2008; Kelso, 1994; Kugler & Turvey, 1988; Newell, 1986), the Russian physiologist Bernstein, proposed that motor behaviour generally and motor learning more specifically could be conceptualized as a problem of solving degrees of freedom (Bernstein, 1996). He argued that a central command system in the brain, like that defined in early ideas of a motor program, would be overwhelmed with the copious degrees of freedom (i.e., independent units or dimensions) that would need to be controlled for successful motor skill execution. For example, in an underarm softball pitch to a batter, at least 20 muscles would require independent specification, at any point of time in the movement.

To overcome the degrees of freedom problem, Bernstein postulated that the first stage of learning essentially involves a constraining or freezing of some degrees of freedom. By fixating certain muscles/joints, or coupling the movement of one muscle or joint to another, such as seen in the inefficient co-contraction of agonist and antagonist muscles around a joint, computational load at any given point in time is reduced. In the softball-pitching example, a novice pitcher can limit the movements in the elbow and wrist joints, relying only on the rotation around the shoulder to generate momentum for ball release. As learning progresses, there would be a ‘freeing’ of these degrees of freedom and an associated increase in independence between joints or muscles. Correspondingly, relative motion of joints involved in a motor task become less coupled and manifest as decreased correlation in relative motion between joints (see Newell & McDonald, 1994; Vereijken, Emmerik, Whiting & Newell, 1992). In the softball-pitching example, we might see a decrease in correlation between the relative motions of the elbow and wrist joints as the pitcher starts to flex the elbow and wrist joints at different moments in the pitch. In the final stage of motor learning, it is proposed that the motor system becomes more mechanically and energy efficient through exploitation of the mechanical-inertial properties of the limbs (e.g., extension of the more proximal shoulder joint would result in passive torques at the more distal elbow and wrist joints). Higher-skilled softball pitchers are more likely to exploit the dynamic interactions between joint motions, activating different muscle groups at different times during the pitching motion, so as to maximize the angular momentum transferred to the ball at release.

Depending on the nature of the task, tighter couplings between joints could also be seen at a more advanced stage of learning. The emergence of coordinative structures, that is relations between components of the motor system that serve a functional purpose, with increasing expertise, might reflect better control of task-relevant versus non-task relevant variability. Couplings that emerge later in practice will be those that matter most for task success (usually the timing and position of distal joints in throwing type actions).

Learning goals

It should be apparent to practitioners that the type of task or goal of learning are important considerations for structuring practice and assessing learning. Motor skills have often been categorized along a continuum of closed to open skills (e.g., Gentile, 1972; Poulton, 1957). Closed skills are motor tasks that are performed in a predictable or stable environment, devoid of variability that would arise from the influence of external factors, while open skills are executed in unpredictable environments subject to external influence.

Retention

If the goal of practice is to learn a closed skill or produce only one variant of a motor skill accurately and consistently, we would be most interested in the performers' long-term retention of the skill. A retention test typically assesses performance of the same task that was executed in practice (Schmidt & Lee, 2011). To enhance learning and best prepare performers to execute the practised task under real-world "test" conditions, the practice context should match the test conditions as closely as possible. This guideline for structuring practice is known as the “specificity of learning” or “practice specificity” principle (e.g., Barnett, Ross, Schmidt & Todd, 1973; Proteau, Marteniuk & Lévesque, 1992). As mentioned in the Section “Primary theories, frameworks and associated concepts” of this chapter, retention tests are usually administered after a period of delay, allowing time for temporary performance influences to dissipate before learning is assessed. Absolute measures of performance at retention, especially when compared with pre-practice levels or control group levels, provide an indication of the extent of (relatively) permanent behavioural changes that have transpired with practice. Relative measures, such as difference scores between the end of practice and retention or percentage change in pre-practice to retention, offer alternative ways of quantifying learning (or forgetting).

Some empirical evidence from research on memory consolidation suggests that skill retention is impacted by the achievement of performance stability (e.g., Hauptmann, Reinhart, Brandt & Karni, 2005). Within a practice session, stability is achieved when the performance curve begins to level out, termed asymptotic performance. In addition to practice amount, we also know that there are many ways of manipulating practice quality to impact retention. Conditions that make practice conditions harder and more effortful are often shown to be the conditions which result in the strongest retention effects (Lee, Swinnen & Serrien, 1994). There is some minor disagreement about whether delayed tests of learning conducted in the absence of a variable present in practice should be called “retention” or “transfer” tests. Regardless of their label, we do know that such tests (e.g., the no-KR retention test) provide valuable information about what has been retained independently from its potential guiding role in practice. As discussed earlier with respect to memory consolidation, events following motor practice can also exert positive or negative effects on retention (e.g., rewards, sleep or subsequent practice of new tasks) (e.g., Fischer et al., 2002; Larssen, Ong & Hodges, 2012; Stickgold, 2005).

Transfer

For motor tasks that are categorized as open skills, a learner’s goal would be to enhance the capacity for response adaptability, which increases the odds that optimal movement solutions would be selected in varying contexts or under varying constraints. Practice protocols that promote problem solving and experience of a variety of movement solutions would allow generalizability across a range of performance contexts. In motor learning studies, the capacity for generalization is assessed through transfer tests (Schmidt & Lee, 2011). Transfer is a critical measure of learning as rarely are the conditions of practice the same as the conditions of test (such as in sports competition or in functional tasks of everyday life following rehabilitation). According to the practice specificity principle, transfer would be elicited with increased similarity between the practice and criterion tasks. These similarities may be in the perceptual-motor elements of the tasks and its performance context, or in the cognitive processes underlying performance of both tasks (also referred to as transfer-appropriate processing, encoding specificity and representative task design; Graf & Ryan, 1990; Lee, 1988; Tulving & Thomson, 1973; Pinder, Davids, Renshaw & Araújo, 2011, respectively).

For increased training fidelity, performers would practise in performance contexts that are identical or as closely matched to test conditions that they would later be tested on (often with added pressure). This type of transfer is referred to as "near" or specific transfer (Schmidt & Lee, 2014). Conversely, transfer effects observed with large disparities between the training environment and a later test phase would be considered "far" or general transfer. In reality, high-fidelity training may be cost-prohibitive, risky or difficult to achieve. For instance, the cost and risks of training fighter pilots to operate a real aircraft is remarkably greater than training in a flight simulator. It is challenging in itself for practitioners to re-create conditions that would be experienced by performers under test or match contexts. Besides an interest in structuring practice for high-fidelity training, researchers and practitioners are also concerned with questions on how "far reaching" the transfer effects of their practice might be. How much dissimilarity can exist between practice and criterion skills, or how closely matched must these conditions be, for transfer effects to be significant and meaningful? Transfer designs allow a probe of what has been acquired and how abstract that learning might be (e.g., if something transfers to the non-practised hand then we know learning was not specific to the muscles involved in the training phase). In this way, transfer tasks help to inform learning theory and can tell us what is acquired and the level of specification of learning.

Transfer can also be considered with respect to how learning episodes of different skills potentially facilitate or impede performance and learning of another skill. Proactive transfer is the term used to describe how previous practice in one activity impacts on performance of a second activity, such as that observed moving from practice playing tennis to squash (Schmidt &

Lee, 2011). Another form of transfer is retroactive transfer. This was previously mentioned in relation to memory consolidation and it describes how the immediate and subsequent practice of a closely related skill could interfere with the performance of a previously practised skill (e.g., how tennis is affected from interspersed practice of squash) (e.g., Krakauer, 2009). Researchers have shown that retroactive interference from practice of a second skill is possible up to 4-5 hours after practice of an initial skill (e.g., Brashers-Krug, Shadmehr & Bizzi, 1996; Press, Casement, Pascual-Leone & Robertson, 2005). The directional influence of transfer can be positive or negative. Positive transfer refers to a facilitative effect and negative transfer indicates interference. Transfer effects, whether positive or negative, may be expected between motor performances in net-type games, such as in tennis and badminton. Positive transfer may result from improved anticipation of an opponent's actions hence leading to more optimal response selection, as comparable tactical decision-making and strategies exist between tennis and badminton. However, there is likely to be negative transfer in stroke execution between the two activities. The badminton forehand consists of a wrist snap, while the tennis forehand typically involves a fixed wrist (except for elite players). Transfer would not be expected from unrelated skills that feature vastly disparate perceptual-motor elements or do not share similar cognitive-related processes.

Skill refinement, relearning and technique change

Much of our discussion of motor learning has been focused on acquisition of new skills, reflecting the general course of research in the field. Yet, performers often find themselves making refinements to their motor responses, whether they are attempting to adjust their movements so that performance may be more accurate, powerful or consistent (e.g., greater use of legs and shorter pole push while double poling in cross country skiing), or adopting a new technique altogether (e.g., Fosbury flop in high jump) while aiming to achieve the same task goal. The ease with which performers are able to effect change or refine a skill appears to be associated with the level of expertise acquired on an existing motor skill.

As discussed earlier, one of the distinguishing characteristics of skilled performance is the extent to which a motor skill is autonomously controlled without demands on attentional resources. Based on this cognitive perspective of motor learning, any modification to movement coordination is arguably easier to accomplish before automaticity is attained. To modify a well-learned skill in a significant manner (also known as shifting, relearning or habit change), it is thought that a performer must first “de-automatize” its control and de-couple existing perceptual-motor associations to avoid spontaneous and undesired production of the old movement pattern in future performance scenarios (Carson & Collins, 2018). Suggested methods to aid movement de-automatization have often included some form of explicit comparing, contrasting and cueing between a “new way” and the “old way” (akin to cognitive processing described in the elaboration hypothesis of the contextual interference effect), followed by extensive practice of the new way until automaticity or stability is achieved (e.g., Lyndon, 1989). Depending on the performance context, a new technique may be acquired to either replace an old one, or as an additional skill to apply in new situations (related to the idea of “bifurcations” in ecological-dynamics, Davids et al., 2008). How well a new skill is learned is influenced by the degree of perceptual-motor and processing similarities between the new and existing skill (see discussion on “transfer”). The greater the similarity between the new and existing skill, the greater the interference or competition between these skills.

Due to the scarcity of research on technique change, questions as to whether an existing movement pattern can actually be replaced by another, or whether closely related techniques can co-exist without competition, remain relatively unanswered. From an ecological dynamics perspective, there is evidence that the learning of a new pattern, coupled with increased stability of this pattern over time, would change the stability of and appearance of behaviours that are “close-by” in terms of coordination demands (e.g., Zanone & Kelso, 1992). This has been referred to as a change in the attractor landscape. One interesting observation in dynamics research based on motor learning of new coordination patterns, is that these attractors might only show up under certain conditions (such as high speeds, high attention demands) (Haken et al., 1985). As such, undesirable movement patterns can be “replaced” but they may not truly be annihilated.

Technique change can be brought about by direct and indirect means, that is through more prescriptive instructional means or through a change to the task constraints forcing adaptation on behalf of the learner. For example, both an abrupt and a gradual introduction of a novel split-belt treadmill pattern (independent belts for each limb that move at different speeds) led to similarly adapted walking patterns in healthy adults (Roemmich & Bastian, 2015). However, the additive effects of an abrupt introduction and extended practice on the novel task enhanced retention of the new walking pattern the most. This suggests that an explicit awareness of task regularities and characteristics distinguishing a new skill might aid the stability and co-existence of both new and old skills.

Summary

In summary, we have defined motor learning and discussed the various ways it has been studied and conceptualized. In addition to thinking about learning at various levels of the motor system, including cognitive-levels, neurophysiological and biomechanical, motor learning has also been considered with respect to principles based on self-organization under constraints as well as in relation to acquisition of memory structures. In motor learning research, considerable evidence has accumulated showing that methods which promote active engagement on the part of the learner during practice, related to variable practice conditions and active problem solving are best for longer term learning. Moreover, when these conditions of practice are most closely matched to conditions where test or transfer is required, the efficacy of the practice will be heightened.

With respect to the history and future of the field, there has been a growing trend for research and associated theories which are rooted in neurophysiology, likely due to the comparative ease today is measuring brain related functioning compared to in the past and because of a growing appreciation of skill acquisition principles for rehabilitation. Schema theory (Schmidt, 1975) has all but been replaced by internal model based frameworks and terminology (e.g., Wolpert et al., 1995), mostly due to a surge in the computational engineering fields, where models of control have been formulated to help explain and potentially engineer adaptive movements in the fields of robotics. In sport, the constraints-based, ecological dynamics framework has had a significant impact in practical coaching settings, although empirical, evidence-based interventions for practice methods and instructions are still mostly based in cognitive frameworks. With improvements in technology and potential for enhanced measurement of actions through wearables, phone apps etc., there is a strong likelihood that principles concerning what to do with information, how to design simulations and how best to promote efficient and effective learning and relearning will continue to be developed and researched. The future of motor learning from an interdisciplinary perspective looks to be rich and vibrant.

References

Adams, J. A. (1971). A closed-loop theory of motor learning. *Journal of Motor Behavior, 3*(2), 111-150.

Anderson, J. R. (1982). Acquisition of cognitive skill. *Psychological Review*, *89*(4), 369-406.

Barnett, M. L., Ross, D., Schmidt, R. A., & Todd, B. (1973). Motor skills learning and the specificity of training principle. *Research Quarterly, 44*, 440-447.

Beilock, S. L., & Carr, T. H. (2001). On the fragility of skilled performance: What governs choking under pressure?. *Journal of experimental psychology: General*, *130*(4), 701-725.

Bernstein, N. A. (1996). On motor control. In M. L. Latash & M. T. Turvey (Eds.), *Dexterity and its Development* (pp. 25-44). Mahwah, NJ: Erlbaum.

Brashers-Krug, T., Shadmehr, R., & Bizzi, E. (1996). Consolidation in human motor memory. *Nature*, *382*(6588), 252-255.

Buonomano, D. V., & Merzenich, M. M. (1998). Cortical plasticity: From synapses to maps. *Annual Review of Neuroscience, 21*(1), 149-186.

Carson, H. J., & Collins, D. (2018). Refining motor skills in golf: A biopsychosocial perspective. In M. Toms (Ed.), *Routledge International Handbook of Golf Science* (pp. 196-206). New York, NY: Routledge.

Carter, M. J., Smith, V., & Ste-Marie, D. M. (2016). Judgments of learning are significantly higher following feedback on relatively good versus relatively poor trials despite no actual learning differences. *Human Movement Science*, *45*, 63-70.

Classen, J., Liepert, J., Wise, S. P., Hallett, M., & Cohen, L. G. (1998). Rapid plasticity of human cortical movement representation induced by practice. *Journal of Neurophysiology*, *79*(2), 1117-1123.

Crocker, P. R. E. (2007). *Sport and exercise psychology: A Canadian perspective*. Toronto, ON: Pearson Canada.

Crossman, E. R. F. W. (1959). A theory of the acquisition of speed skill. *Ergonomics*, *2*(2), 153-166.

Davids, K. W., Button, C., & Bennett, S. J. (2008). *Dynamics of skill acquisition: A constraints-led approach*. Champaign, IL: Human Kinetics.

Deci, E. L., & Ryan, R. M. (2000). The" what" and" why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, *11*(4), 227-268.

Diedrichsen, J., Hashambhoy, Y., Rane, T., & Shadmehr, R. (2005). Neural correlates of reach errors. *Journal of Neuroscience*, *25*(43), 9919-9931.

Edelman, G.M., & Gally, J. (2001). Degeneracy and complexity in biological systems. *Proceedings of the National Academy of Sciences*, *98*, 13763–13768.

Fischer, S., Hallschmid, M., Elsner, A. L., & Born, J. (2002). Sleep forms memory for finger skills. *Proceedings of the National Academy of Sciences*, *99*(18), 11987-11991.

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

Gentile, A. M. (1972). A working model of skill acquisition with application to teaching. *Quest*, *17*(1), 3-23.

Graf, P., &Ryan, L. (1990). Transfer-appropriate processing for implicit and explicit memory. *Journal of Experimental Psychology: Learning, Memory, & Cognition,16*, 978–992.

Gray, R. (2004). Attending to the execution of a complex sensorimotor skill: expertise differences, choking, and slumps. *Journal of Experimental Psychology: Applied*, *10*(1), 42-54.

Guadagnoli, M. A., Holcomb,W. R., & Weber, T. (1999). The relationship between contextual interference effects and performer expertise on the learning of a putting task. *Journal of Human Movement Studies, 37*, 19–36.

Guadagnoli, M. A., & Kohl, R. M. (2001). Knowledge of results for motor learning: relationship between error estimation and knowledge of results frequency. *Journal of Motor Behavior*, *33*(2), 217-224.

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

Haken, H., Kelso, J. S., & Bunz, H. (1985). A theoretical model of phase transitions in human hand movements. *Biological Cybernetics*, *51*(5), 347-356.

Hauptmann, B., Reinhart, E., Brandt, S. A., & Karni, A. (2005). The predictive value of the leveling off of within session performance for procedural memory consolidation. *Cognitive Brain Research*, *24*(2), 181-189.

Holroyd, C. B., & Coles, M. G. (2002). The neural basis of human error processing: reinforcement learning, dopamine, and the error-related negativity. *Psychological Review*, *109*(4), 679-709.

Hosp, J. A., Pekanovic, A., Rioult-Pedotti, M. S., & Luft, A. R. (2011). Dopaminergic projections from midbrain to primary motor cortex mediate motor skill learning. *The Journal of Neuroscience*, *31*(7), 2481-2487.

Huang, V. S., Haith, A., Mazzoni, P., & Krakauer, J. W. (2011). Rethinking motor learning and savings in adaptation paradigms: model-free memory for successful actions combines with internal models. *Neuron*, *70*(4), 787-801.

Huang, V. S., & Shadmehr, R. (2007). Evolution of motor memory during the seconds after observation of motor error. *Journal of Neurophysiology*, *97*, 3976-3985.

Ito, M., Yamaguchi, K., Nagao, S., & Yamazaki, T. (2014). Long-term depression as a model of cerebellar plasticity. *Progress in Brain Research*, *210*, 1-30.

Karni, A., Meyer, G., Rey-Hipolito, C., Jezzard, P., Adams, M. M., Turner, R., & Ungerleider, L. G. (1998). The acquisition of skilled motor performance: fast and slow experience-driven changes in primary motor cortex. *Proceedings of the National Academy of Sciences*, *95*(3), 861-868.

Keele, S. W. (1968). Movement control in skilled motor performance. *Psychological Bulletin*, *70*, 387-403.

Kelso, J. A. S. (1994). The informational character of self-organized coordination dynamics. *Human Movement Science*, *13*(3-4), 393-413.

Krakauer, J. W. (2009). Motor learning and consolidation: the case of visuomotor rotation. In D. Sternad (Ed.), *Progress in Motor Control* (pp. 405-421). Springer US.

Kugler, P. N., & Turvey, M. T. (1988). Self-organization, flow fields, and information. *Human Movement Science*, *7*(2-4), 97-129.

Larssen, B. C., Ong, N. T., & Hodges, N. J. (2012). Watch and learn: seeing is better than doing when acquiring consecutive motor tasks. *PloS One*, *7*(6), e38938.

Latash, M.L. & Turvey, M.T. (1996). Dexterity and its development (with On Dexterity and Development by N.A. Bernstein, 1896-1966). Mahwah, NJ : L. Erlbaum Assoc.

Lee, T. D. (1988). Transfer-appropriate processing: A framework for conceptualizing practice effects in motor learning. *Advances in Psychology*, *50*, 201-215.

Lee, T. D., & Magill, R. A. (1983). The locus of contextual interference in motor-skill acquisition. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *9*(4), 730-746.

Lee, T. D., Swinnen, S. P., & Serrien, D. J. (1994). Cognitive effort and motor learning. *Quest*, *46*(3), 328-344.

Lyndon, H. (1989). Research into practice. *Australasian Journal of Special Education, 13*, 32–37.

Masters, R. S., & Maxwell, J. P. (2004). Implicit motor learning, reinvestment and movement disruption: what you don't know won't hurt you. In A. M. Williams & N. J. Hodges (Eds.), *Skill Acquisition in Sport: Research, Theory and Practice* (pp. 207-228). New York, NY: Routledge.

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

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.

McGaugh, J. L. (2000). Memory--a century of consolidation. *Science*, *287*(5451), 248-251.

Muellbacher, W., Ziemann, U., Wissel, J., Dang, N., Kofler, M., Facchini, S., ...Hallett, M. (2002). Early consolidation in human primary motor cortex. *Nature*, *415*(6872), 640-644.

Newell, K. M. (1986). Constraints on the development of coordination. In M. G. Wade & H. T. A. Whiting (Eds.), *Motor development in children. Aspects of coordination and control* (pp. 341-360). Dordrecht, Netherlands: Martinus Nijhoff.

Newell, K. M., & McDonald, P. V. (1994). Learning to coordinate redundant biomechanical degrees of freedom. In S. P. Swinnen, H. Heuer. J. Massion & P. Casaer (Eds.), *Interlimb Coordination: Neural, Dynamical, and Cognitive Constraints* (pp. 515-536). Academic Press.

Newell, A., & Rosenbloom, P. S. (1981). Mechanisms of skill acquisition and the law of practice. In J. R. Anderson (Ed.), *Cognitive Skills and their Acquisition*, NJ: Erlbaum.

Nissen, M. J., Willingham, D., & Hartman, M. (1989). Explicit and implicit remembering: When is learning preserved in amnesia?. *Neuropsychologia*, *27*(3), 341-352.

Ong, N. T., Bowcock, A., & Hodges, N. J. (2010). Manipulations to the timing and type of instructions to examine motor skill performance under pressure. *Frontiers in Psychology, 1*: 196.

Ong, N. T., Lohse, K. R., & Hodges, N. J. (2015). Manipulating target size influences perceptions of success when learning a dart-throwing skill but does not impact retention. *Frontiers in Psychology, 6*: 1378.

Pinder, R. A., Davids, K., Renshaw, I., & Araújo, D. (2011). Representative learning design and functionality of research and practice in sport. *Journal of Sport and Exercise Psychology*, *33*, 146-155.

Poulton, E. C. (1957). On prediction in skilled movements. *Psychological Bulletin*, *54*(6), 467-478.

Press, D. Z., Casement, M. D., Pascual-Leone, A., & Robertson, E. M. (2005). The time course of off-line motor sequence learning. *Cognitive Brain Research*, *25*, 375-378.

Proteau, L., Marteniuk, R. G., & Lévesque, L. (1992). A sensorimotor basis for motor learning: Evidence indicating specificity of practice. *The Quarterly Journal of Experimental Psychology*, *44*, 557-575.

Roemmich, R. T., & Bastian, A. J. (2015). Two ways to save a newly learned motor pattern. *Journal of Neurophysiology*, *113*, 3519-3530.

Schmidt, R. A. (1975). A schema theory of discrete motor skill learning. *Psychological Review*, *82*(4), 225-260.

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

Schmidt, R. A., & Lee, T. D. (2014). *Motor Learning & Performance: From Principles to Application* (5th ed). Champaign, IL: Human Kinetics.

Schneider, W., & Shiffrin, R. M. (1977). Controlled and automatic human information processing: I. Detection, search, and attention. *Psychological review*, *84*(1), 1-66.

Seidler, R. D. (2010). Neural correlates of motor learning, transfer of learning, and learning to learn. *Exercise and Sport Sciences Reviews*, *38*(1), 3-9.

Seidler, R. D., Kwak, Y., Fling, B. W., & Bernard, J. A. (2013). Neurocognitive mechanisms of error-based motor learning. Advances in Experimental Medicine and Biology, 782, 39-60.

Shadmehr, R., & Holcomb, H. H. (1997). Neural correlates of motor memory consolidation. *Science*, *277*(5327), 821-825.

Shea, C. H., & Kohl, R. M. (1991). Composition of practice: Influence on the retention of motor skills. *Research Quarterly for Exercise and Sport, 62*, 187-195.

Shea, J. B., & Morgan, R. L. (1979). Contextual interference effects on the acquisition, retention, and transfer of a motor skill. *Journal of Experimental Psychology: Human Learning and Memory*, *5*(2), 179-187.

Shea, J. B., & Zimny, S. T. (1983). Context effects in memory and learning movement information. In R. A. Magill (Ed.), *Memory and Control of Action* (pp. 345-366). Amsterdam: Elsevier.

Stickgold, R. (2005). Sleep-dependent memory consolidation. *Nature*, *437*(7063), 1272-1278.

Sullivan, K. J., Kantak, S. S., & Burtner, P. A. (2008). Motor learning in children: feedback effects on skill acquisition. *Physical therapy*, *88*(6), 720-732.

Taylor, J. A., & Ivry, R. B. (2014). Cerebellar and prefrontal cortex contributions to adaptation, strategies, and reinforcement learning. *Progress in Brain Research*, *210*, 217-253.

Tulving, E., & Thomson, D. M. (1973). Encoding specificity and retrieval processes in episodic memory. *Psychological Review, 80,* 359-380

Van Rossum, J. H. A. (1990). Schmidt’s schema theory: The empirical base of the variability of practice hypothesis. *Human Movement Science, 9*, 387–435.

Vereijken, B., Emmerik, R. E. V., Whiting, H. T. A., & Newell, K. M. (1992). Free(z)ing degrees of freedom in skill acquisition. *Journal of Motor Behavior*, *24*(1), 133-142.

Wadden, K. P., Borich, M. R., & Boyd, L. A. (2012). Motor skill learning and its neurophysiology. In N. J. Hodges & A. M. Williams (Eds.), *Skill Acquisition in Sport: Research, Theory and Practice* (pp. 247-265). New York, NY: Routledge.

Winstein, C. J., & Schmidt, R. A. (1990). Reduced frequency of knowledge of results enhances motor skill learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition,* 16, 677-691.

Wolpert, D., Ghahramani, Z., & Jordan, M. (1995). An internal model for sensorimotor integration. *Science, 269*, 1880-1882.

Wolpert, D. M., Miall, R. C., & Kawato, M. (1998). Internal models in the cerebellum. *Trends in Cognitive Sciences*, *2*(9), 338-347.

Wulf, G. (2013) Attentional focus and motor learning: A review of 15 years. *International Review of Sport and Exercise Psychology, 6*(1), 77-104.

Wulf, G., & Lewthwaite, R. (2016). Optimizing performance through intrinsic motivation and attention for learning: The OPTIMAL theory of motor learning. *Psychonomic Bulletin & Review*, *23*(5), 1382-1414.

Wulf, G., McNevin, N., & Shea, C. H. (2001). The automaticity of complex motor skill learning as a function of attentional focus. *The Quarterly Journal of Experimental Psychology: Section A*, *54*(4), 1143-1154.

Zanone, P. G., & Kelso, J. A. (1992). Evolution of behavioral attractors with learning: Nonequilibrium phase transitions. *Journal of Experimental Psychology: Human Perception and Performance, 18*(2), 403-421.