Strategy processes in sensorimotor learning: Reasoning, Refinement, and Retrieval.

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Abstract

Motor learning has traditionally been viewed as a unitary process that operates outside of conscious awareness. This perspective has led to the development of sophisticated models designed to elucidate the mechanisms of implicit sensorimotor learning. In this review, we argue for a broader perspective, emphasizing the contribution of explicit strategies in simple sensorimotor learning tasks, and how these insights underpin a comprehensive model of strategy use in complex motor skills. As a starting point, we propose three general strategic processes: Reasoning, the process of understanding action-outcome relationships; Refinement, the process of optimizing sensorimotor and cognitive parameters to achieve the motor goal; and Retrieval, the process of inferring the context and recalling a control policy. We anticipate that this 3R framework for understanding the role of explicit strategies in motor learning will open exciting avenues for future research at the intersection between cognition and action.

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I. The contribution of strategy use in a wide range of simple sensorimotor learning tasks

Glance through any neuroscience textbook and motor learning, the process of refining our movements through feedback and practice, will be described as an implicit, non-declarative phenomenon (Figure 1). Indeed, this description matches the phenomenology of skilled performers who "let the body do the thinking" when executing a highly practiced motor skill (Jackson, 1996). In the domain of cognitive science, foundational work motivating this perspective stems from the classic studies with Patient H.M., an individual who had undergone bilateral medial temporal lobectomy and subsequently developed severe anterograde amnesia (Scoville & Milner, 1957). Despite having no recollection of performing a mirror drawing task, H.M. exhibited striking improvements over multiple sessions of practice (Milner, 1962). This monumental finding helped inspire taxonomies of human learning and memory that place motor learning squarely in the domain of "implicit memory" (Squire, 2004; Squire & Zola-Morgan, 1991).

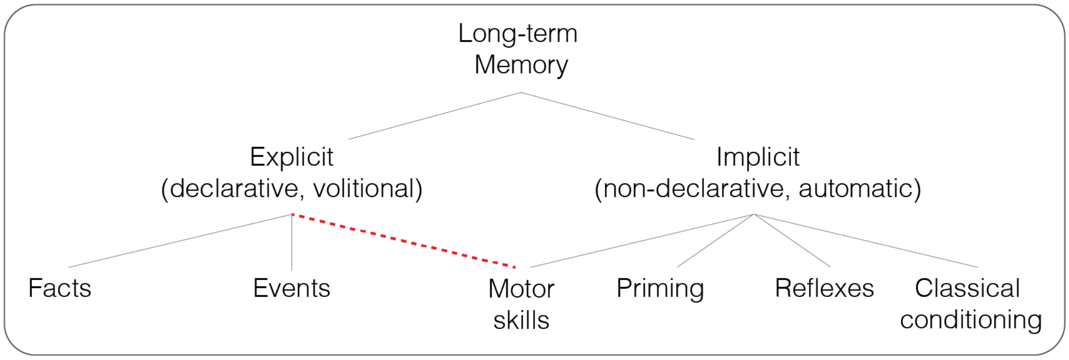

Figure 1. Classic and revised taxonomies of long-term memory. A revision of the classic taxonomy proposed by Squire and Zola (1996) (grey lines), with motor skills tapping into both explicit and implicit memory (dashed red line).

This simplified perspective overlooks a crucial distinction: While H.M. may not have retained *explicit memory of learning* between sessions, he may well have employed *explicit strategies for learning* within each session (Krakauer et al., 2019). Recent research provides compelling evidence in support of this hypothesis, showing not only the operation of multiple learning processes during mirror drawing, but also that the explicit component of learning is the primary impetus for improvement (Wilterson & Taylor, 2021). Indeed, experts can make rapid and flexible motor corrections, suggesting that even when behavior seems automatic, there remains considerable cognitive control. More generally, it would be difficult to find a motor skill that does not require the application of explicit strategies (Stanley & Krakauer, 2013).

Broadly speaking, a division can be made between implicit learning and explicit strategy. Implicit learning plays a crucial role in executing well-calibrated movements, a non-declarative process that operates automatically and outside of conscious awareness (Mazzoni & Krakauer, 2006; R. Morehead et al., 2017; Tsay et al., 2020). Conversely, explicit strategy is responsible for selecting and planning movements, a declarative process that operates under volitional control (Deng et al., 2022; Hegele & Heuer, 2010; H. E. Kim et al., 2020; Lillicrap et al., 2013; McDougle et al., 2016; Ryan Morehead & de Xivry, 2021; Seidler & Carson, 2017; Taylor et al., 2014; Werner et al., 2015).

Error-based motor learning, the process of refining movements through vectorial sensory feedback, has provided the most comprehensive test bed for characterizing the contribution of multiple learning processes (Anguera et al., 2010; Benson et al., 2011; Bromberg et al., 2019; Coltman et al., 2021; de Brouwer et al., 2018; Haith et al., 2015; Huberdeau et al., 2015; H. E. Kim et al., 2020; Taylor et al., 2014). Traditionally, error-based learning has been characterized by implicit changes in heading angle (i.e., reach direction) in response to perturbed sensory feedback (e.g., Figure 2A; rotation of the visual feedback) (Held & Hein, 1958; Helmholz, 1909). These implicit changes in heading remain robust (also known as "aftereffects") even when perturbed sensory feedback is removed, and participants are instructed to forgo strategy use and reach directly toward the visual target.

However, two key pieces of evidence highlight the prominence of error-based explicit strategies in these tasks. First, while participants can successfully adapt to large perturbations such as a visual rotation of 45°, the aftereffect is considerably smaller, consistent with the hypothesis that only a fraction of the learning was implicit (Figure 2B) (Taylor et al., 2014). Second, when asked to verbally report where they intended to aim before each movement, participants' explicit reports clearly showed that a large portion of learning was driven by explicit strategies. Together, these findings elevate error-based motor learning from a process placed squarely in the domain of implicit memory to one that also relies on explicit declarative strategies.

Explicit strategies also contribute to other error-based adaptation tasks, such as saccade adaptation (J. Huang et al., 2017), force-field adaptation (Schween et al., 2020), target-jump adaptation (Sadaphal et al., 2022), prism adaptation (Leukel et al., 2015; Prablanc et al., 2020; Redding & Wallace, 2002) and locomotor adaptation (Ellmers et al., 2020; Malone & Bastian, 2010; Roemmich et al., 2016). Speech adaptation is one domain where an explicit component has yet to be found; indeed, characteristic of implicit learning, the degree of speech adaptation tends to be limited and incomplete, with changes in performance only amounting to ~50% of the total perturbation (K. S. Kim & Max, 2021; Lametti et al., 2020; Munhall et al., 2009; Parrell et al., 2021).

One of the most compelling cases for strategy use is found in **mirror-reversal learning** (Ewert, 1930; Sekiyama et al., 2000; Stratton, 1897; Sugita, 1996; Telgen et al., 2014). Introspection when performing the task underscores both the significant cognitive demands required and the ready adoption of strategy use (e.g., "To go left, move right."). More recently, efforts have been made to quantify the relative contribution of implicit and explicit components to mirror-reversal learning (Figure 2C) (Hadjiosif et al., 2020; Lillicrap et al., 2013; Wilterson & Taylor, 2021; Yang et al., 2021). Based on verbal reports about the intended aiming position, over 90% of the learning originates from an explicit strategy (Figure 2D). Additionally, the substantial time required for movement planning (Wilterson & Taylor, 2021), as well as learning impairments observed under dual-task conditions (Eversheim & Bock, 2001) all indicate that mirror reversal learning relies heavily on strategy use.

Multiple learning processes also contribute to **reinforcement-based motor learning**, the process of refining movements through reward and/or punishment. In the initial work with this method, learning was thought to occur via implicit processes (Cashaback et al., 2019; Galea et al., 2015; Izawa & Shadmehr, 2011; Nikooyan & Ahmed, 2015; Uehara et al., 2019; Wu et al., 2014). However, reinforcement-based motor learning engages both implicit and explicit processes: As illustrated in Figure 2E-F, participants can successfully adjust their movements based on binary reinforcement feedback signaling whether their movements hit or missed a hidden, and gradually shifting, reward zone (van Mastrigt et al., 2023). Strikingly, less than 50% of learning can be attributed to implicit processes, as indexed by the aftereffect phase when participants are instructed to forgo strategy use and reach directly toward the visual target. This result underscores the significant contribution of strategy use in reinforcement-based motor learning.

Two additional pieces of evidence emphasize the presence of reinforcement-driven sensorimotor strategies. First, unlike error-based vectorial feedback (Block & Bastian, 2011; Ruttle et al., 2021; Tsay, Kim, et al., 2021), binary reinforcement does not distort the participants' sense of hand position, strengthening the claim that the sensorimotor map is not implicitly altered by reward and/or punishment (Izawa & Shadmehr, 2011). Second, learning is severely compromised when the task is performed concurrently with a secondary task, indicating that reinforcement-based motor learning can be cognitively demanding (Codol et al., 2018; Holland et al., 2018). Together, these findings make a strong case for strategy use during reinforcement-based motor learning.

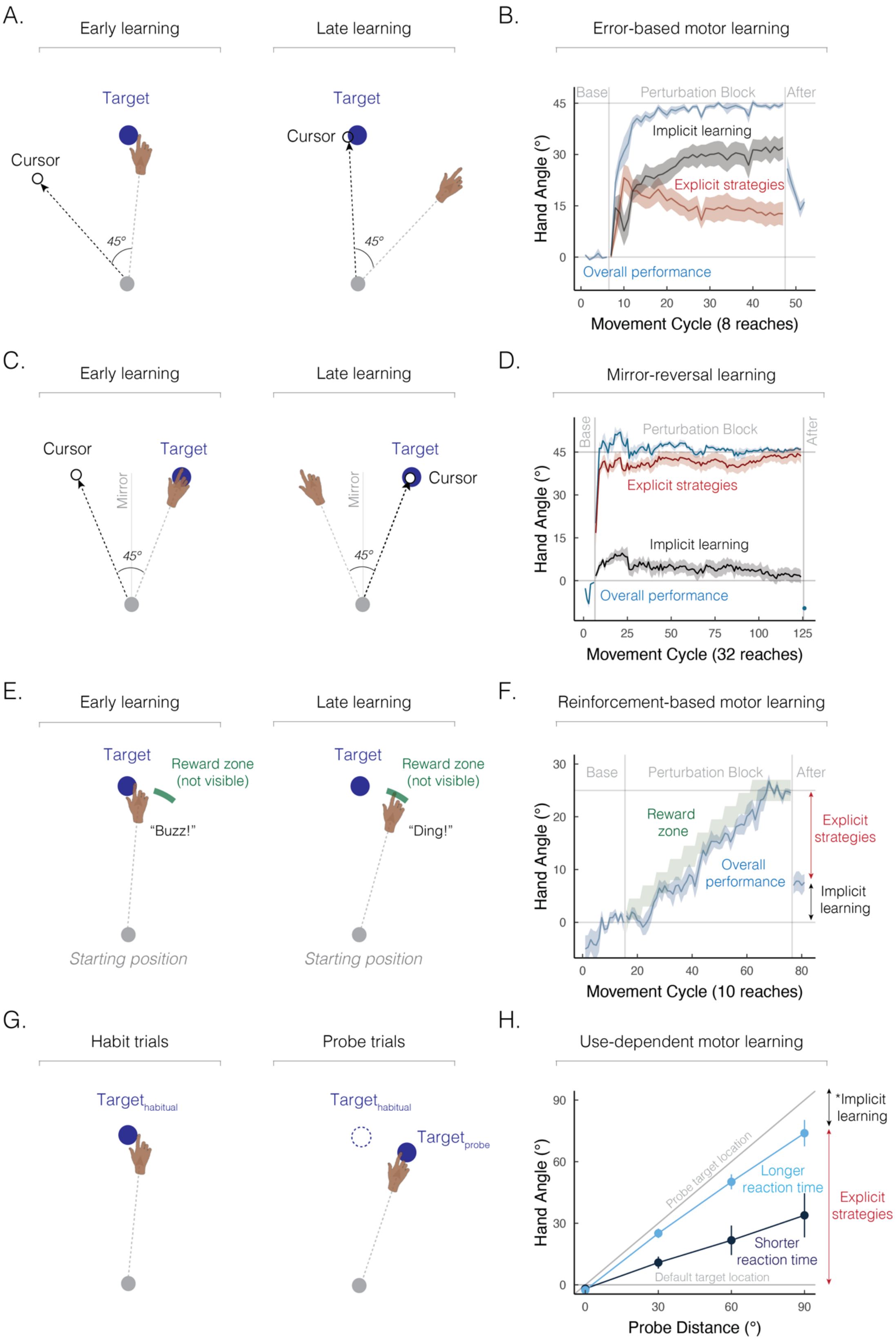
A.
Early learning
Late learning
Target
Cursor
45°
B.
Error-based motor learning
Base
Perturbation Block
After
Implicit learning
Explicit strategies
Overall performance
Hand Angle (°)
45
30
15
0
0
10
20
30
40
50
Movement Cycle (8 reaches)
C.
Early learning
Late learning
Cursor
Target
Mirror
45°
D.
Mirror-reversal learning
Base
Perturbation Block
After
Explicit strategies
Implicit learning
Overall performance
Hand Angle (°)
45
30
15
0
0
25
50
75
100
125
Movement Cycle (32 reaches)
E.
Early learning
Late learning
Target
Reward zone (not visible)
"Buzz!"
"Ding!"
Starting position
F.
Reinforcement-based motor learning
Base
Perturbation Block
After
Reward zone
Overall performance
Explicit strategies
Implicit learning
Hand Angle (°)
30
20
10
0
0
20
40
60
80
Movement Cycle (10 reaches)
G.
Habit trials
Probe trials
Target habitual
Target probe
H.
Use-dependent motor learning
*Implicit learning
Probe target location
Longer reaction time
Explicit strategies
Shorter reaction time
Default target location
Hand Angle (°)
90
60
30
0
0
30
60
90
Probe Distance (°)

Figure 2. Multiple processes contribute to a wide range of sensorimotor learning tasks. A) Schematic of an error-based motor learning task. The 45° rotated cursor feedback (white dot) was provided throughout the movement. **B)** Mean time courses of hand angle (light blue line) during baseline veridical feedback (cycles 1 – 6), error-based feedback (cycles 7 – 47), and no-feedback aftereffect cycles (cycles 48 - 52). Red line denotes the time course of strategy use, measured by verbal reports of aiming location using a number wheel. Black line denotes the time course of implicit learning, estimated by subtracting verbal reports of aiming location from overall performance. Figure adapted from Taylor et al (2014). **C)** Schematic of a mirror-reversal task. The visual cursor feedback (white dot) was reflected over the vertical axis and provided throughout the movement. **D)** Mean time courses of hand angle (light blue line) during baseline veridical feedback (cycles 1 – 6), error-based feedback (cycles 7 – 125), and a no-feedback aftereffect cycle (cycle 126). Red line denotes the time course of strategy use, measured by verbal reports of aiming location using a number wheel. Black line denotes the time course of implicit learning, estimated by subtracting verbal reports of aiming location from overall performance. Figure adapted from Wilterson & Taylor (2021). **E)** Schematic of a reinforcement-based motor learning task. Participants made center-out reaching movements from a grey starting circle to the blue target. A pleasant auditory "ding" was provided when the movement passed within the reward zone (green arc); otherwise, an unpleasant "buzz" was played. **F)** Gradually changing the reward zone (green zone) leads to learning (light blue line), as indicated by the change in hand angle. Hand angle is presented relative to the target (0°) during baseline veridical feedback trials (cycles 1-15), reinforcement feedback (cycles 16-75), and no-feedback aftereffect trials (cycles 76 - 80). Figure adapted from van Mastright et al (2023). **G)** Schematic of a use-dependent motor learning task. Participants reached a habitual target in 80% of the trials; in the remaining 20% of the trials, participants reached one of six probe targets located between 0° - 90° away from the default target. **H)** Participants exhibited a marked use-dependent bias towards the default target on probe trials (i.e., failure to re-aim away from the default target), with the size of this bias modulated by reaction time (medium split). Reaches with faster reaction times exhibited greater biases (black line), whereas reaches with slower reaction times exhibited smaller biases (light blue line). Grey lines denote reaches toward the default (horizontal line) and probe target location (diagonal line). *Implicit use-dependent biases, when statistically isolated, are less than 5° for all probe distances. Figure adapted from Tsay*, Kim*, et al (2022). Shaded error bars denote SEM.

Multiple learning processes also play a role in **use-dependent motor learning**, the process of refining movements through repetition, independent of feedback (Classen et al., 1998; Mawase et al., 2017). For example, in reaching studies, use-dependent learning is evident as a bias towards a frequently performed movement direction (Diedrichsen et al., 2010; Verstynen & Sabes, 2011). This movement bias is believed to be implicit and rigid, meaning it cannot be flexibly overridden by explicit, declarative processes. However, recent findings have demonstrated that a large portion of use-dependent bias can be explicitly overridden (Marinovic et al., 2017; Reuter et al., 2019; Tsay, Kim, Saxena, et al., 2022) (but see: (Suleiman et al., 2023; Wong & Haith, 2017)): As illustrated in Figure 2G-H, the use-dependent bias towards a frequently repeated movement (i.e., default target location) is more pronounced for faster and more impulsive movements, while the bias is reduced for movements initiated slower and more cautiously. This finding highlights how explicitly re-aiming towards a different motor goal (i.e., the probe target location) can effectively override a default motor plan (i.e., the default target location).

Beyond the sensorimotor learning tasks outlined above, consideration of multiple processes is also important for understanding **motor sequence learning** (see (Krakauer et al., 2019) for an in-depth review). The serial reaction time task has been widely deployed as a test of implicit learning. However, even the earliest studies using this task demonstrate that explicit learning can have a major effect on performance, impacting how participants represent the structure of the sequence (Cohen et al., 1990; Jiménez et al., 2006; Nissen & Bullemer, 1987). Moreover, even under conditions designed to minimize explicit learning, participants, including those with severe anterograde amnesia, develop explicit knowledge of sequence fragments. This explicit knowledge is, in fact, essential for performance improvements, accounting for much of the reduction in reaction time (Moisello et al., 2009; Reber & Squire, 1994, 1998).

New psychophysical methods have proven useful in identifying properties of implicit and explicit learning processes across multiple dimensions (Table 1; also see (Huberdeau et al., 2015) focusing on a subset of these dimensions). Similar to how implicit and explicit processes have been dissociated in other domains (Batterink et al., 2015; Turk-Browne et al., 2005), implicit sensorimotor learning is minimally impacted by variations in cognitive demand such as the time available for planning (Haith et al., 2015; Leow et al., 2017), whereas strategy use is very sensitive to cognitive load, a process negatively impacted when planning time is limited (Fernandez-Ruiz et al., 2011).

More germane to the motor domain, implicit learning is sensitive to the timing of feedback, relying on a close temporal association between movement initiation and feedback presentation (Kitazawa et al., 1995; Schween & Hegele, 2017; Wang et al., 2022). Implicit learning also operates in an invariant manner in response to a wide range of perturbations (H. E. Kim et al., 2018; Marko et al., 2012; R. Morehead et al., 2017; Tsay, Lee, et al., 2021; Wei & Körding, 2009) and is not modulated by the variability of the perturbation (Avraham et al., 2020; Wang & Ivry, 2023) (but see (Albert et al., 2021)). In contrast, strategy use remains robust even when the feedback is significantly delayed (Brudner et al., 2016; Tsay, Schuck, et al., 2022), scales with the size of the perturbation (Krista Bond & Taylor, 2015), and is attenuated when the perturbation is unpredictable (Hutter & Taylor, 2018).

The two processes also differ in terms of savings and generalization. Implicit learning is attenuated upon re-learning, whereas explicit strategies show savings (Avraham et al., 2021; Haith et al., 2015; R. Morehead et al., 2015; Tsay et al., 2023). Implicit learning exhibits narrow generalization around the aiming location (Day et al., 2016; Krakauer et al., 2000; R. Morehead et al., 2017), minimal generalization across effectors (Poh et al., 2016), and is based in both extrinsic and intrinsic coordinate frames (Poh & Taylor, 2019). (Note: Extrinsic coordinate frames are linked to the physical world, while intrinsic coordinate frames are linked to the state of the body (Hudson & Landy, 2016; Sober & Sabes, 2005).) Strategy use results in broad generalization to different target locations (McDougle et al., 2017; McDougle & Taylor, 2019; Poh et al., 2021), exhibits almost full generalization to other effectors (Bouchard & Cressman, 2021; Werner et al., 2019), and is based primarily in extrinsic coordinate frames (Poh & Taylor, 2019).

Strikingly, the effect of aging has opposite effects on these two processes: While implicit learning is either similar or enhanced in older adults compared to younger adults, strategy use is markedly impaired (Ruitenberg et al., 2023; Tsay et al., 2023; Vandevoorde & Orban de Xivry, 2019, 2020; Wolpe et al., 2020).

#	**Dimension**	**Implicit Learning**	**Explicit Strategy**
1	Declarative	No	Yes
2	Volitional	No	Yes
3	Planning time	Short	Long
4	Computational goal	Minimize sensory prediction error	Minimize task error
5	Feedback timing	Sensitive	Insensitive
6	Perturbation size	Saturates for large errors	Scales with error size
7	Perturbation variability	Insensitive	Sensitive
8	Perturbation re-learning	Attenuation	Enhancement
9	Spatial generalization	Narrow	Broad
10	Effector generalization	No	Yes
11	Coordinate generalization	Extrinsic and intrinsic	Mostly extrinsic
12	The effect of aging	Enhancement	Attenuation

Table 1. Implicit and explicit sensorimotor learning processes differ along many psychological, task, and demographic dimensions.

II. The 3R Framework for Strategy Use: Reasoning, Refinement, and Retrieval

The principles of implicit and explicit learning processes have been most convincingly established in simple sensorimotor learning tasks, those that require only minutes to learn (e.g., see examples in Section I). We expect that analogous principles will apply to the acquisition of complex motor skills – those that require hours, days, and even weeks to learn (Du et al., 2022; Haith et al., 2022; Listman et al., 2021; Nah et al., 2020; Scholz et al., 2009). However, understanding complex sensorimotor strategies will be a considerable challenge, one that will likely require new computational principles and insights.

Early computational models of sensorimotor learning were grounded in the assumption that motor learning operates as a unitary implicit process. One prominent model (i.e., single-rate state-space model) proposed that motor learning follows a gradual and iterative process that seeks to minimize sensory prediction error (Donchin et al., 2003; Shadmehr et al., 2010), the discrepancy between the predicted and actual feedback. However, this model fails to capture key behavioral features such as the rapid drop in performance during the aftereffect phase when participants are instructed to reach directly to the target (Figure 1).

These failures led to revised models that recognized the behavior was comprised of multiple learning processes (Haruno et al., 2001; Herzfeld et al., 2014; V. S. Huang et al., 2011; H. E. Kim et al., 2020; Lee & Schweighofer, 2009; McDougle et al., 2015). Revised multi-rate state-space models have assumed either multiple sensory prediction error-driven mechanisms (Smith et al., 2006), multiple task error-driven mechanisms (Albert et al., 2022), or distinct error-based mechanisms, with one sensitive to sensory prediction error and the other sensitive to task error (Taylor & Ivry, 2011; Tsay, Haith, et al., 2022). Although these models often successfully capture the average group behavior (Figure 3A) (Cisneros et al., 2023), they fail to account for idiosyncratic individual learning profiles that deviate from gradual error reduction (Taylor & Ivry, 2011). Specifically, a comprehensive account of strategy use would need to explain why individuals show punctuated jumps in behavior (Figure 3B; “moments of insight”), marked and varied exploratory patterns (Figure 3C), and systematic errors that are inconsistent with gradual error reduction (Townsend et al., 2023). Furthermore, a good model would need to explain why the sign of the error systematically flips in early learning (Figure 3D) (McDougle & Taylor, 2019) or why performance systematically worsens in response to certain perturbations (Hadjiosif et al., 2020; Kasuga et al., 2015; Telgen et al., 2014).

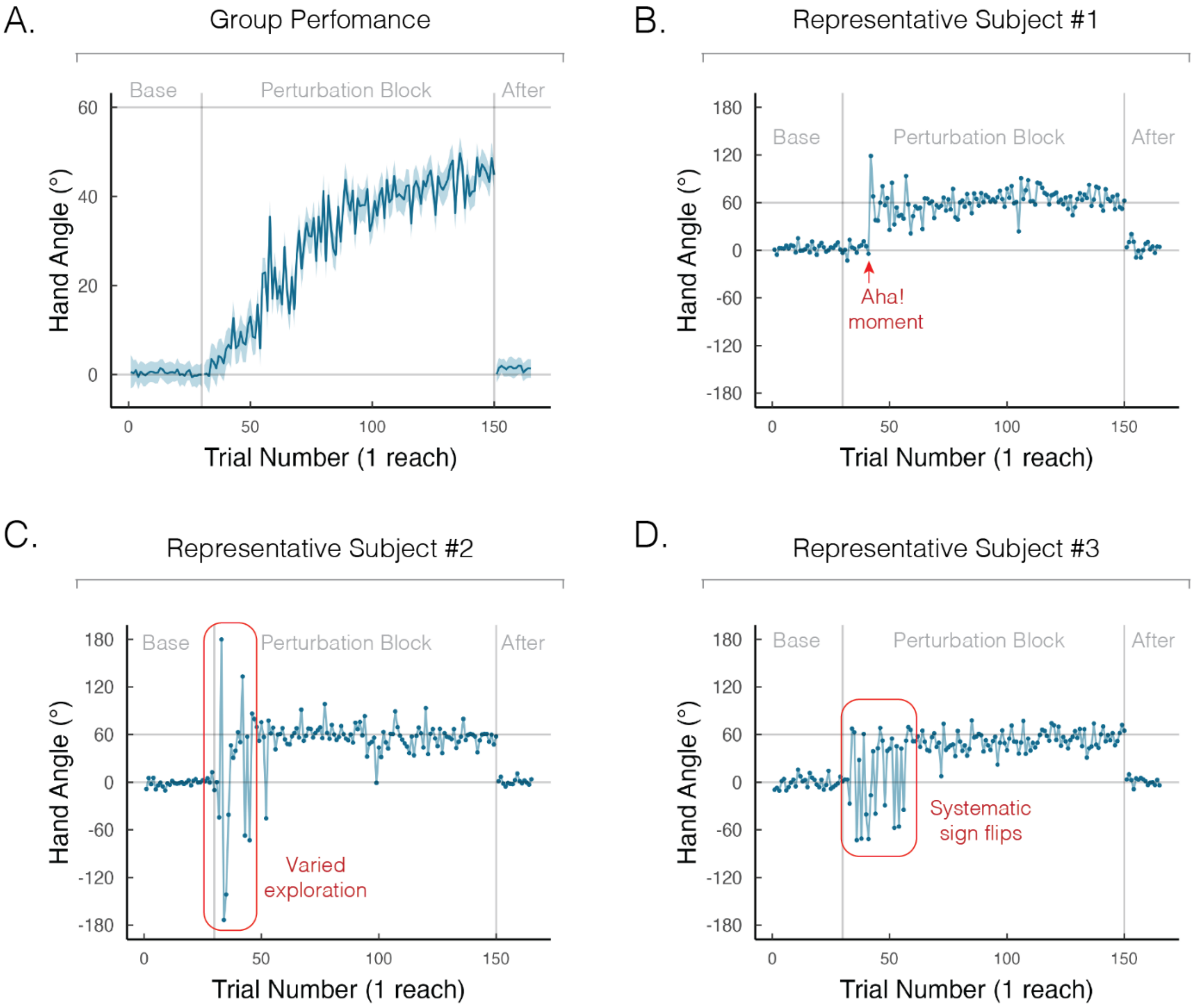

Figure 3. Group and representative individual performance in an error-based learning task. A) Median time course of heading angle during baseline veridical feedback (trials 1 – 30), error-based perturbed feedback (trials 31 – 150), and no-feedback aftereffect trials (trials 151 – 165). During the perturbation phase, a 60° rotated endpoint cursor feedback (white dot) was provided. To isolate strategy use and abolish implicit adapation, visual feedback was provided 800 ms after movement termination. Indeed, motor aftereffects, a signature of implicit adaptation, was not evident in the participants' data. Shaded error bars denote SEM. **B - D)** Representative individuals exhibiting **B)** moments of insight, **C)** varied early exploration, and **D)** systematic sign flips of ±60°. Figures adapted from Cisneros, et al (2023).

To make progress toward a formal computational account of strategy use in complex real-life motor skills, it will be crucial to consider three general processes: Reasoning, Refinement, and Retrieval ("3R" framework). **Reasoning** involves understanding (often arbitrary) action-outcome relationships and using this knowledge to construct an effective controller (A. Collins & Koechlin, 2012; Donoso et al., 2014; Heald et al., 2021; Lillicrap et al., 2013; Todorov & Jordan, 2002; Yang et al., 2021). To illustrate this concept, consider learning to ride a bicycle. One of the initial steps for the novice is to understand the relationship between movements of the arm and movements of the bicycle. Once the novice identifies the correct action-outcome relationship, she can leverage this physical intuition to derive a crude control policy (e.g., (Allen et al., 2020)).

Motor learning researchers can draw valuable insights from cognitive science, a field that has formalized computational models for reasoning. For example, one flavor of reasoning is "Inference over Hypotheses"

(Griffiths et al., 2010; Piantadosi et al., 2016; Rule et al., 2020; Xia & Collins, 2021), which entails two main components: First, the hypothesis space encompasses domain-specific action primitives and relational primitives. Action primitives may entail movements such as “moving the right arm forward” or “moving the left arm backward,” while relational primitives may encompass operations like “or,” “and,” “before,” and “after.” By combining these primitives, more complex hypotheses can be created, such as “moving the right arm forward and the left arm backward will move the bike leftward.” Second, the merits of these hypotheses can be evaluated via inference, where learners use sensory feedback to strengthen or weaken their beliefs about each hypothesis.

Reasoning as inference has a few advantages over classic models of motor learning. First, it can account for behaviors inconsistent with gradual error reduction. For example, marked exploratory behavior early in learning and punctuated jumps in behavior may signify the rapid modification and adoption of action-outcome hypotheses; errors may show systematic sign flips when the novice mistakes the direction of a rotation as clockwise instead of counterclockwise; and errors may systematically increase when a novice pursues incorrect hypotheses, such as mistaking a mirror reflection for a rotation. Second, reasoning as inference goes beyond learning which affine transformation (e.g., rotation, translation, reflection, etc.) best explains the action-outcome relationship (e.g., (Baddeley et al., 2003; Burge et al., 2008; Wei & Körding, 2010)). Specifically, cognitive hypotheses may be more abstract and qualitative in nature. As such, the hypothesis space can be more expansive, comprising a near-infinite combination of action-relational primitives; the process of learning can also be more elaborate, involving non-parametric and non-linear computations (e.g., particle filters and Gaussian processes) that might be necessary for mastering complex motor skills. (Heald et al., 2021; Therrien et al., 2016).

We recognize that there are many ways to strategically reason: Inferential reasoning seeks to understand which set of primitives best explains the action-outcome relationship (e.g., “How should I best coordinate my arms to make a leftward turn?”), whereas abductive reasoning seeks to identify the most plausible cause (e.g., “Did moving my right arm forward and left arm backward cause the bike to turn left?”). Novices may also prefer computationally cheaper, heuristic ways of reasoning. For example, they may rely on working memory to develop a control policy that avoids recent unsuccessful actions and repeats successful actions (A. Collins, 2018; A. G. E. Collins et al., 2017; A. G. E. Collins & Frank, 2012). Future studies are needed not only to determine which type of reasoning provides a more suitable explanation for strategy use in different tasks but also to explore other reasoning processes that help break down a complex motor skill into more learnable subcomponents.

Refinement entails learning the optimal movement parameters to achieve the motor goal. Building on the previous example, once our novice cyclist understands how manipulation of the handlebars controls the bike’s heading angle, she needs to refine this skill, learning the optimal timing and amplitude of the movements for different types of turns. This is a crucial phase where learners fine-tune their control policy to achieve movement goals in an accurate, precise, and efficient manner. The process of strategy use can be viewed as a process of utility maximization (Wolpert & Landy, 2012; Yoon et al., 2020), with the inputs to the utility function varying based on task requirements. Through utility maximization, the learner will progressively converge on the optimal movement parameters that enable her to expertly maintain a consistently smooth and stable bike ride.

Contrary to classic models of motor learning, which often solely focus on maximizing sensorimotor utilities like accuracy (Kording & Wolpert, 2004), precision (Shmuelof et al., 2012), and energy conservation (Abram et al., 2022, 2019; Finley et al., 2013; Sánchez et al., 2017), a comprehensive model of strategy refinement will need to consider how both sensorimotor *and* domain-general utilities are jointly refined. Here, too, motor learning researchers can draw valuable insights from cognitive science, a field that has formalized models for how domain-general utilities contribute to learning. These domain-general utilities include intrinsic motivation (Kulkarni et al., 2016; Molinaro & Collins, 2023; Wulf & Lewthwaite, 2016), financial incentives (Lebreton et al., 2018), cognitive effort (Frömer et al., 2021; Koranda et al., 2022), sense of agency (Haggard, 2017; Parvin et al., 2018), sense of embodiment (Kieliba et al., 2021; Schone et al., 2023), informativeness (Barack et al., 2023), and social praise (Mueller & Dweck, 1998).

Concretely, by parametrically manipulating different utility functions and providing participants with explicit movement goals (i.e., minimizing the need for strategic reasoning), we can observe how sensorimotor and cognitive utilities may dynamically trade-off during learning. For instance, during early learning, participants may move accurately but with significant cognitive effort, whereas in late learning, they may allow for more errors in exchange for reduced cognitive effort (K. Bond et al., 2021). Together, we envision that this approach will take us one step closer to understanding how humans learn complex motor skills, where numerous sensorimotor and cognitive control utility functions are optimized in a multivariate and interactive manner (Ritz et al., 2022).

Retrieval entails recalling a control policy to efficiently achieve the motor goal. Once a cyclist has refined the strategy for maintaining a steady bike ride, the control policy becomes embedded in memory and, with appropriate contextual cues, can be retrieved in the future (Heald et al., 2021; Xia & Collins, 2021). For example, when our expert biker encounters a set of stairs, she can rapidly maneuver her bike to execute a flawless "Wheelie Drop" (i.e., a stunt trick where the biker lifts the front wheel off the ground while moving down the stairs).

Cross-pollination between cognitive science and motor learning has fostered the development of several computational models of retrieval. These models formalize how learners use contextual information (e.g., sensory cues and bodily states) to retrieve the appropriate control policy for accomplishing a goal (Eckstein & Collins, 2020; Gershman et al., 2010; Heald et al., 2021, 2023; Xia & Collins, 2021). These models generally consist of three components: First, the learner possesses a memory of various contexts, with each context associated with a control policy. For example, when heading out a smooth well-paved trail, a mountain biker might adopt a narrow, aerodynamic position to increase speed, whereas to start down a rocky descent, the biker might shift to the back edge of the seat to adopt a more stable position. Second, the learner continuously makes contextual inferences from a stream of sensory cues. For example, if our biker starts feeling friction against her wheels, she might infer, with some uncertainty, that she is encountering a heavily forested section. If none of the contextual memories match the current context, the learner may create a new memory associated with a new control policy, one that can undergo further reasoning and refinement. Third, the learner makes an action based on an integrated control policy (e.g., a weighted average of context-specific control policies determined by their similarity to the current context).

How is motor expertise – the ability to enact complex movements with efficiency, accuracy, and consistency (Du et al., 2022; Ericsson, 2014) – viewed through these three general components of retrieval? First, experts likely possess a wealth of contextual memories associated with a given motor task, each with a well-reasoned and well-refined control policy acquired through extensive practice and experience. Second, experts avoid creating entirely new memories and control policies, as this process is likely computationally demanding. Instead, they can efficiently and confidently match the current context with a specific one in memory. Third, experts need not tediously evaluate the merits of different control policies. Instead, they have forged strong associations between contexts and control policies, which enable them to easily and unambiguously enact a well-reasoned, refined, and successful action tailored to the current context. While future experiments are needed to directly contrast these retrieval processes between novices and experts, we foresee that these ideas will open exciting avenues to advance theories of skill acquisition and inform the design of training programs to enhance expertise.

It is important to recognize that while strategic performance is volitional and explicit, the 3Rs of strategy use may function at different points along the implicit-explicit continuum. Even though we can verbalize and consciously control our movements during a use-dependent learning task, we may be unaware that the sensorimotor system has retrieved a highly practiced default response, especially when preparation time is limited. Similarly, while we can consciously aim away from the displayed target in visuomotor rotation and mirror reversal tasks, we may have difficulty explaining our strategy (Maresch et al., 2021) or identifying the utility functions we sought to maximize (McAllister et al., 2021). Thus, the 3R framework invites us to move beyond simple implicit-explicit *dichotomies* and consider how strategic changes in performance may emerge from learning mechanisms at different points along the implicit-explicit *continuum* (also see: (Hadjiosif & Krakauer, 2021; Maresch et al., 2020)).

With this graded and more nuanced perspective, we revisit the intriguing phenomenon observed in the performance of H.M. when tested on a mirror drawing task over multiple sessions. Despite having no memory of having performed the task in prior sessions, H.M. showed excellent retention. Interestingly, this retention was effector-specific, meaning that left-hand performance only benefited from previous left-hand practice, and vice versa. On one hand, these data suggest that the benefits observed in H.M.'s performance were due to context-dependent strategic recall, where the context is defined by the movement effector. On the other hand, the improvements in H.M. may instead be attributed to improved strategy refinement. That is, within each session, H.M.'s use of a strategy becomes refined in an effector-specific manner and this benefit is retained across sessions. Future empirical studies are needed to evaluate this possibility, shedding light on the dynamic interplay between recall and refinement in learning motor skills.

The 3R framework shares similarities with the classic skill acquisition framework proposed by Fitts and Posner (Fitts & Posner, 1979). The Fitts-Posner framework describes three stages of learning: The cognitive, associative, and automatic stages. In the cognitive stage, the novice grasps an understanding of the goals of the task and the general structure of the actions required to achieve that goal. In the associative stage, the novice experiments with different gestures, learning the different movement subcomponents that form the skilled action. Finally, the automatic stage captures how the skill becomes refined, with the expert moving in an effortless and near-reflexive manner.

While the 3R and Fitts-Posner frameworks both acknowledge that the acquisition of motor skills involves a transition from being cognitively demanding to automatized, there are two notable differences. First, the Fitts-Posner framework describes motor skill acquisition at a purely phenomenological level. In contrast, the 3R framework outlines specific computational mechanisms. For example, as a starting point, we outlined how reasoning relies on inference and/or heuristics, refinement is driven by utility maximization, and retrieval depends on contextual inference. We anticipate that this level of computational specificity will inspire more concrete experimental tests that can advance motor learning research.

Second, the Fitts-Posner framework emphasizes a singular progression through the cognitive, associative, and automatic stages of learning, with a focus on how motor memories that are initially declarative becomes proceduralized with practice. In contrast, the 3R framework not only takes as a starting point that motor skills involve the operation of multiple learning processes, but its computational emphasis also facilitates easy integration with other learning processes. While reasoning, refinement, and retrieval constitute one route toward successful motor learning, these processes can be readily combined with other computational mechanisms, such as those for implicit learning (e.g., (Tsay, Kim, Haith, et al., 2022)). This feature is crucial, as it highlights the importance of characterizing learning processes with distinct dynamics and constraints (Table 1).

III. Forging a Stronger Bond between Cognition and Action

We have demonstrated the important, yet underappreciated role of explicit strategy use in sensorimotor learning. Consequently, there has been little progress in the development of models for explicit strategy. Here, we present a framework that postulates how successful strategy use relies on three general processes: Reasoning, Refinement, and Retrieval. As these ideas advance toward a formal computational account, we see opportunities for increased cross-pollination between motor learning and cognitive science communities. Undoubtedly, these intellectual bonds will be essential for developing a comprehensive theory of motor learning, capable of explaining the intricate cognitive-motor interactions that facilitate successful motor skill acquisition, adaptation, and retention.

IV. Open questions

1. How do reasoning, refinement, and retrieval differ across motor learning tasks? For example, how do action-outcome hypotheses and utility functions differ between skills that are part of our natural development (e.g., reaching, walking) and those that may be acquired at a later age (e.g., knitting, ballroom dancing)?

2. Neuropsychological findings suggest that the prefrontal cortex and cerebellum may play a role in reasoning but not in refinement or retrieval (Butcher et al., 2017; McDougle et al., 2022; Taylor & Ivry, 2014; Tsay, Schuck, et al., 2022; Wong et al., 2019). Are other brain areas involved in strategy retrieval but not reasoning? More generally, how are reasoning, refinement, and retrieval implemented in the brain?

3. What are the behavioral and neural constraints underlying the transition between deliberate and automatic motor skills (Fresco et al., 2022; Servant et al., 2018)? Does automaticity reflect a reliance on retrieval-based mechanisms or is there also a need to consider the role of strategy refinement?

4. How can the 3R framework inform physical rehabilitation for patients with movement disorders? How do individual features such as age, physical fitness, and different cognitive abilities (Anderson et al., 2021; Anguera et al., 2010; Guo & Song, 2023; Tsay et al., 2023) impact reasoning, refinement, and retrieval?

5. How are strategic reasoning, refinement, and retrieval impacted by changes in context (Avraham et al., 2022; Dawidowicz et al., 2022; Forano et al., 2021; Heald et al., 2021)?

6. Where are strategic reasoning, refinement, and retrieval positioned on the implicit/explicit continuum? How does the implicit-explicit nature of these processes change with sensorimotor experience?

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