“Watch It, Try It” Loops:
The Neuroscience of Learning a New Skill

By Steven Shaw
August 2, 2025

There is a universal experience in skill acquisition, a sequence so common that every student and instructor is familiar with it. An instructor demonstrates a complex task or maneuver—a perfect landing flare, a fluid steep turn, a precise stall recovery. The student watches intently, processing the sequence of events. When it’s over, they nod, confirming their understanding, and say something along the lines of “okay, that makes sense”. They have grasped the logic of the task.

Then comes the attempt. The student takes the controls, and the execution is predictably clumsy. It is disjointed, jerky, lacking the flow and precision of the demonstration. The instructor then initiates the next phase of the learning process with a simple instruction: “Okay, watch again”.

The student observes the same demonstration for a second time. But this time, something different happens. A look of profound understanding dawns on their face—the universal “Ohhhhh” moment. It is a palpable click of insight, a moment where the previously hidden details suddenly snap into focus. When the student takes the controls for their next attempt, their performance is markedly improved.

This familiar sequence is not a happy accident or a mystery of talent. It is a window into the brain’s fundamental learning process. The neurological process that makes the second viewing so much more potent than the first is what I refer to as the “Watch It, Try It” loop. This article deconstructs the specific, observable neuroscience that drives this powerful learning algorithm.

The Brain’s Learning Algorithm

The Initial Blueprint

The “Watch It, Try It” loop is effective because it taps directly into the brain's innate architecture for learning. The process begins with our ability to learn by watching, a capacity facilitated by a remarkable network of brain cells known as the **Mirror Neuron System**. These neurons are unique in that they fire both when we perform an action and when we watch someone else perform that same action. A simple, universal example of this process is when we feel the urge to yawn after seeing someone else do it. Our brains simulate the actions we observe.

This simulation process is the biological foundation of observational learning. However, for a complex skill, this initial blueprint is always low-resolution. A simple yawn is one thing; a maneuver like a landing flare involves a cascade of coordinated control inputs, sensory cross-checks, and decisions that cannot be fully captured in a single viewing, especially without the corresponding physical sensations.

When a student observes an instructor's demonstration, their brain uses this imperfect, low-resolution blueprint as the raw material for its first predictive model.

In this context, a predictive model is the brain's internal simulation of the skill. It's not just a static memory of the steps, but a dynamic forecast of the internal structural relationships involved with executing the task. It predicts the specific sensory consequences—what it will look like, feel like, and sound like—that should result from a given sequence of motor commands. It's the brain's attempt to answer the question, "If I do this, what will happen next?"

Because this initial predictive model is built from scratch, with no prior experience or feedback to guide the brain's attention, it is built upon a "best guess" of what is important. This leads to two fundamental kinds of flaws in the model's architecture:

First, the brain commits **Hierarchical Errors** because it doesn't understand the ranking or importance of the skill's components. In attempting to grasp the overall sequence of a task, a novice brain defaults to a primitive, "bottom-up" attentional process, where its focus is automatically captured by the most neurologically stimulating cues—a rapid movement, a sudden sound, or a bright flash of light. An expert, by contrast, uses "top-down" control, leveraging their experience to consciously direct their attention. They learn to pay less attention to these more obvious, though often less relevant, elements and instead focus on the subtle, interconnected patterns that are truly fundamental to correct task execution.

Second, the brain makes **Relational Errors**, failing to correctly model the internal structural relationships of the skill. It struggles to map the complex interactions between cues, actions, and outcomes. The result is a flawed internal schematic where the right steps may be linked to the wrong information or executed in the wrong sequence. For instance, in certain situations, a novice pilot might form a simplistic relational model that causes them to be overly focused on the Vertical Speed Indicator (VSI) to correct an altitude deviation, when an expert's more sophisticated model would prioritize the Attitude Indicator to make a smoother, more precise correction.

This structurally unsound model, built on incorrect priorities and flawed relationships, is what characterizes the clumsy, error-filled performance of a beginner and is why refinement through the "Try It" phase is the essential next step for skill development.

Refining the Model Through Error

Refining this initial, low-resolution model is the critical next step in the learning process. This happens through the Prediction-Error Cycle, a process of testing and correction driven by the "Try It" phase.

When the brain sends a motor command to execute the skill, it simultaneously sends an internal duplicate of that command to its own sensory regions. This signal, called an **efference copy**, creates a prediction of what the movement *should* feel and look like. The existence of this predictive signal is not just theoretical; it's demonstrated by the simple fact that you cannot tickle yourself. When you try, your brain's efference copy perfectly predicts the resulting sensation, and the brain cancels it out. When someone else tickles you, there is no predictive efference copy, and the raw, unpredicted sensation is registered.

During a student's clumsy first attempt at a new task, the *actual* sensory feedback from their body and eyes inevitably mismatches the prediction generated by the efference copy. This mismatch creates a powerful, biological signal known as a **Prediction Error**. This is not a feeling of disappointment; it is a quantifiable neural event that alerts the brain that its current prediction model is flawed. This process generates an internal **error model**—a specific understanding of what went wrong. This phenomenon is physically measurable and observable; EEG studies can detect a distinct electrical signature, the Mismatch Negativity (MMN) wave, when the brain registers a violation of a predicted pattern.

This is what makes a new demonstration so powerful. The brain, now armed with a specific error model, is no longer just building a blueprint from scratch; it is actively updating its predictive model using the correct demonstration as a guide. This begins an iterative process of refinement, where the brain's focus shifts from using primitive, bottom-up cues to grasp the overall sequence to instead hunting for the specific data needed to resolve the errors it just experienced.

During this process, it begins to correct its **Hierarchical Errors**. It starts to perceive the more subtle, interconnected patterns that are truly fundamental to success, which requires learning to pay less attention to the obvious, high-stimulus cues that may ultimately be less critical.

Simultaneously, it starts to rewire its **Relational Errors**, correcting the flawed internal structural relationships it had formed. This targeted search makes previously unseen details neurologically **salient**—that is, they "stand out" as highly important. Guided by its error model, the brain has now flagged these details as the specific solutions to the problems it needs to solve. The cognitive experience of refining the predictive model into a more coherent structure is what leads to the student's "Ohhhhh" moment of insight.

The Beginner's Bottleneck

The prediction-error cycle is the engine of learning, but it is constrained by a hard limit in our brain's architecture. The process of actively learning a new skill happens in our **working memory**, a mental workbench where we consciously process information. According to **Cognitive Load Theory**, this workbench is incredibly small. Modern research suggests it can only handle about three to four new **"points of conscious control"** at any one time. These are the individual, discrete elements of a new skill that a person must actively think about in order to perform them.

For a beginner, every discrete step of a complex maneuver—a specific control input, a visual check, a procedural step—is a separate point of conscious control that occupies a slot in their limited working memory. This is the beginner's bottleneck. Attempting to demonstrate a long, multi-step sequence to a novice immediately overwhelms their cognitive capacity, making it neurologically impossible for them to build a useful predictive model from an initial demonstration.

The Solution—Chunking and Automaticity

The brain's elegant solution to this bottleneck is a process known as **chunking**. This is the mechanism of fusing multiple, separate points of conscious control into a single, seamless, and efficient motor program. In effect, a "chunk" is a high-fidelity predictive model for a sub-skill that the brain can execute as a single unit.

The "Watch It, Try It" loop is the engine that builds these chunks. With each iterative cycle, the neural pathways connecting the individual control points are physically strengthened and insulated, becoming faster and more efficient until they effectively merge. This is a reflection of key fundamental brain functions like synaptogenesis, myelination, dendritic arborization, and Hebbian learning, for example. As a small part of the skill becomes more integrated and "chunked," it becomes more automated and consumes less working memory. This freed-up cognitive bandwidth is precisely how a student can perceive more detail on each subsequent "Watch It, Try It" loop. Their brain now has the available capacity to process a new, more subtle detail that it was literally blind to during previous demonstrations.

The ultimate outcome of running the "Watch It, Try It" loop repeatedly is to eventually achieve **automaticity**. This is the point at which an entire complex skill has become a single, robust chunk. When a skill achieves automaticity, it no longer occupies a "point of conscious control" slot in working memory. It is managed by the fast, high-capacity subconscious motor system, running in the background with minimal conscious oversight. This is what is commonly referred to as "muscle memory," or the point at which a skill becomes "second nature." This is the ultimate payoff of effective training, as it frees the pilot's limited conscious attention for more critical, higher-order tasks, like maintaining situational awareness and "staying ahead of the aircraft."

Application: Engineering the Learning Event

The Problem with In-Flight Demonstrations

Knowing the brain's hard-wired limitations, we can now see that first-time demonstrations in flight are ultimately neurologically inefficient and almost always result in clumsy, error-filled student performance. For a student who is still building a predictive model from scratch, the cockpit is an environment of overwhelming sensory input. This includes what is known as proprioceptive "noise." Proprioception is the body's sense of its own position and movement; each acceleration and vibration in an aircraft is a force that acts on every single cell of the body, all of which the brain must constantly process. Add to this the drone of the engine, the rush of the wind, and the unpredictable chatter of radio communications, and the student is faced with a cacophony of sensory data that must be filtered, most of which is irrelevant to the specific skill being demonstrated.

This combination of inputs creates a massive cognitive load that floods a novice's limited working memory. When an instructor performs a demonstration against this backdrop of sensory chaos, the student has virtually no cognitive bandwidth left to build a useful predictive model of the skill being taught. The demonstration itself gets lost in the noise.

Worse, the subsequent "Try It" attempt occurs under the real-time pressure of live flight—a true dynamic environment, where the aircraft continues to move regardless of what the pilot does or doesn't do. When the student inevitably makes a mistake in this environment, their cognitive system is already so saturated that it struggles to generate and process a clean error model. The failure is experienced as overwhelming task saturation, not as a clear data point for learning.

Facilitating the Loops

This cognitive reality explains the explosive success of learning platforms like YouTube. At its core, YouTube is an ecosystem built on providing the human brain with exactly what it needs to learn. Traditional manuals, with their static text and diagrams, are a low-bandwidth and abstract medium for conveying a dynamic skill. They can describe the "what," but they struggle to show the "how"—the timing, flow, and interaction between elements. This is why, when trying to acquire a new skill, people instinctively seek out video, which provides rich, dynamic data delivered in a low-load environment, allowing them to develop a much more detailed and sophisticated predictive model than any other medium.

Unlike a one-time live demonstration, a video can be manipulated. A learner can pause to reflect, rewind to study a critical moment, or use slow-motion to deconstruct a rapid sequence of events. They can watch the video one time focusing on a specific element, watch it again focusing on a different element, and then a third time watching how those things fit together. This control over the pace of the demonstration allows the learner to manage the flow of new information, ensuring their working memory is never overloaded.

This deep, interactive analysis is what allows a student to build a high-quality predictive model across all **Five Components of Skill**, a framework detailed in my paper, *"The Right Stuff: Redefining How to Train Pilots."* It enables them to deconstruct everything from the practical application of **Knowledge** and the unfolding of a **Decision-Making** process to the visual and audible patterns of **Perception**, the precise **Physicality** of a control input, and the specific phrasing of **Communication**.

This ability to control the demonstration allows a learner to create their own on-demand "Watch It, Try It" loops with virtually unlimited repetition. A person can watch a demonstration, go attempt the task themselves, and then immediately return to the video to analyze their performance against the correct model—generating and resolving prediction errors on their own time. While a live instructor provides intangible, critical advantages—such as providing real-time feedback and guiding a student's focus during a demonstration—there is still tremendous benefit to the unlimited looping that video provides. It allows the learning and refinement process to continue long after the formal training event is over, turning a single lesson into a source of countless powerful learning "Watch It, Try It" cycles.

In light of this framework, the instructor's primary role is to facilitate the "Watch It, Try It" loop. Knowing the brain's limits, their first job is to deconstruct complex skills into small, manageable components, a method known as **part-task training**. They then lead the student through iterative cycles of demonstration and attempt.

This is not a rigid one-demo, one-try process. A skilled instructor understands that the goal of the "Watch It" phase is to establish a predictive model sufficient for a meaningful attempt by the student. This may require demonstrating the skill several times, or pieces of the skill separately, before the student's first try. Subsequently, the student may need several repetitions in the "Try It" phase, guided by targeted feedback, to develop a clear understanding of their performance gap and form a meaningful error model. Once that error model is sufficiently formed, the student is primed for a new "Watch It" demonstration. This iterative approach stands in contrast to traditional one-time "demo/do" training activities, which fail to leverage the brain's need for a new demonstration to update its predictive model based on the error model it just generated.

While the instructor facilitates the real-time "micro-loops" during a training event, video is an incredibly powerful tool for executing the learning "macro-loop" that occurs between training events. One of the most powerful applications of this is the review of one's own flight footage. After a flight, the newly recorded video becomes the ultimate data source for analysis. The student can compare their actual performance against their intention, allowing them to further refine their error model developed during the flight and subsequently update their predictive model in anticipation for their next flight. This method of learning directly from your own mistakes is an incredibly effective training tool, as it generates the strongest possible Prediction Error signals for the brain to use in refining its predictive model. This is because the review of one's own flight is a multi-sensory event; it pairs the objective visual data from the footage with the brain's own kinesthetic memory of how it felt at the time the errors occurred.

Additionally, footage from other pilots serves as a valuable source of "Watch It" demonstrations. In the specific context of this learning loop, watching a video of other pilots executing a maneuver or task enables the building or refinement of a predictive model before an initial or subsequent "Try It" attempt. This video-powered process allows a student to run countless refinement cycles of their predictive model, leveraging footage—both their own and that of others—as a rich source of data for the next training session.

Conclusion

Anyone thinking about how to apply this intensive looping process will immediately recognize the practical challenges of doing so in the aircraft. The constraints of time, fuel, cost, and the high-load environment of live flight make extensive, real-time "Watch It, Try It" cycles quite impractical. Those people are absolutely correct. This practical limitation is not a flaw in the learning model; it is the central problem that a modern training system must address and overcome. This is precisely why a structured framework is necessary to apply these neurological principles effectively.

The "Watch It, Try It" Loop is not a training gimmick or a matter of preference; it is a direct application of the brain's fundamental, hard-wired algorithm for acquiring and refining complex skills. Understanding this neurological mechanism allows us to intentionally accelerate and optimize the learning process. By applying this knowledge, we can become active engineers of human skill development, designing learning events that are precisely compatible with how the brain actually works to maximize the efficiency of every training event.

This neurological process is the scientific foundation for the Training Loops, a framework detailed in “The Right Stuff”. Each phase of that framework is engineered to leverage a specific aspect of the brain’s learning algorithm:

- **Follow-Along** is designed to build a robust initial predictive model from recordings in a low-load environment. This process leverages the mirror neuron system to establish the neurological foundation of anticipation, all while bypassing the cognitive overload of a first-time, in-cockpit demonstration.
- **Drill** is the ideal **part-task training** setting, creating a controlled environment for running the rapid “Watch It, Try It” micro-loops on specific skill chunks.
- **Do** represents the ultimate “Try It” phase—“game time” where the refined predictive model is tested under real-world conditions, generating the highest-fidelity performance data for post-flight error model analysis and refinement.

This entire framework is designed to systematically apply the cognitive science of learning, using the “Watch It, Try It” loop as the granular engine for building skill with maximum efficiency and speed.

Ultimately, the “Watch It, Try It” loop is powerful because it is the brain’s own language for learning. The greatest gains in performance are found not just in more hours, but in a more precise skill development process. By leveraging the science of how we learn, we can replace guesswork with a repeatable process, take control of our own skill development, and begin to train in a way that is truly compatible with our own neurology. And while this framework is presented through the lens of aviation, it is the fundamental roadmap for acquiring any complex skill, offering a clear path for any dedicated learner to achieve true mastery and maximize their full potential.