Analysis of Dance Teaching Behavioral Methods in the Context of Cognitive Modelling

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ABSTRACT This study investigates dance teaching behavioral methods through the framework of cognitive modeling, employing the Adaptive Control of Thought–Rational (ACT-R) architecture and embodied cognition theory to analyze cognitive-motor learning processes. The research examines how instructional behaviors, including repetition, demonstration, feedback timing, and multimodal cueing, influence memory activation, procedural learning, and skill acquisition. ACT-R simulations and behavioral analyses were conducted to evaluate the effects of different instructional strategies on learning efficiency, movement accuracy, and retention. Results indicate that spaced feedback and multimodal instruction significantly enhance cognitive encoding, motor learning, and long-term skill retention compared with traditional experience-based approaches. The proposed framework is also relevant to training environments that require complex human–machine interaction and procedural skill development, including engineering education in communication, electromagnetic, and antenna-related disciplines. By integrating cognitive science with behavioral instruction, this study provides a systematic methodology for optimizing teaching effectiveness and personalized learning in complex skill-training scenarios.

INDEX TERMS cognitive modeling, ACT-R, embodied cognition, engineering education

I. INTRODUCTION

DANCE, as both an art form and patterned bodily movement, constitutes a complex motor, cognitive, and sensory activity. It involves learning and performing organized sequences that require rhythm, memory, spatial awareness, and bodily control. Dance teaching is inherently a cognitive-motor process, engaging students in information processing, transforming it into motor responses, and conditioning these responses through practice and feedback [1]. Unlike most subjects in the school curriculum, dance instruction is both brain and body-intensive, necessitating sophisticated coordination between cognitive and physical domains. Dance educators employ a range of behavioral teaching methods, including visual modeling, repetition, scaffolding, guided discovery, and various forms of feedback—verbal, tactile, and visual. These practices are traditionally transmitted through experiential exercises rather than being derived from cognitive science models. Although these methods are beneficial to some extent, they are variable and sometimes dogmatic in managing learners' cognitive load and memory styles. Reliance on intuitive and occasionally rigid behavioral techniques fails to adequately account for learners' cognitive limitations, especially in motor skill encoding, recall, and automation [2].

A significant gap in dance pedagogy is the limited application of formal cognitive modeling in the development and evaluation of teaching methods. Despite advances in artificial intelligence and cognitive science, models such as Adaptive Control of Thought–Rational (ACT-R) and principles of embodied cognition have not been extensively utilized in dance instruction, although their potential to streamline and enhance pedagogy is considerable. These models simulate mechanisms of memory, attention, goal processing, and motor control during learning tasks, providing predictive insights into the acquisition and retention of movement sequences [3,4].

ACT-R is a modular cognitive architecture that supports real-time decision-making and skill acquisition. Its subcomponents—declarative memory, procedural memory, and motor output—are directly applicable to dance, where learning entails memorizing, processing, and producing sequential motor actions under time constraints [5]. Embodied cognition posits that cognition is intrinsically linked to sensory and motor experiences, emphasizing the role of body-environment interactions in structuring learning [6].

The objective of this paper is to address this gap by investigating dance teaching behavioral practices within the framework of cognitive modeling, employing ACT-R and embodied cognition as foundational theories. This approach decomposes typical teaching behaviors (e.g., feedback spacing, repetition, mirroring, and task segmentation) into cognitive learning processes, for elucidating how instructional methods affect motor skill acquisition and process memory in complex tasks such as operating advanced automated looms. The study seeks to answer two primary questions:

1) How do specific teacher behaviors influence the cognitive-motor learning of dance?

2) Do ACT-R and embodied cognition adequately model and predict the efficiency of learning in dance instruction?

II. LITERATURE REVIEW

A. DANCE TEACHING BEHAVIORAL METHODS

Dance pedagogy has long employed a variety of behavioral techniques to facilitate motor learning alongside aesthetic skill development. The command technique, wherein the teacher establishes an activity and students imitate, is the most prevalent. It is effective for organizing structure and synchronization, especially in group choreography settings [7]. The guided discovery method enables students to experiment with diverse movement forms within defined boundaries, fostering innovative solutions to movement challenges. This is frequently combined with kinesthetic modeling, through which students emulate body positions demonstrated by instructors or peers to learn motor patterns [8].

Repetition forms the foundation of most pedagogical approaches in dance, supporting the development of muscular memory and movement fluency. Instructors typically divide complex choreography into manageable segments to prevent cognitive overload. This fragmentation aligns with the chunking principle in cognitive psychology, whereby smaller portions are more readily encoded and processed [9]. Imitation is particularly crucial for novice students, who learn by observing the correct execution of movement patterns, timing, and emotional expression.

A significant pedagogical challenge in dance is managing cognitive load, especially during demanding choreography. Students must concurrently address stylistic interpretation, limb coordination, temporal timing, and spatial placement. Without balanced pacing or organized feedback, students may experience cognitive overload, resulting in memory interference and performance breakdown [10]. These challenges underscore the need for scaffolded, cognition-based learning models, wherein behaviorist approaches are informed by models of procedural encoding, working memory, and attention.

B. BEHAVIORAL THEORIES IN SKILL INSTRUCTION

Dance pedagogy is empirically grounded in behavioral psychological models, where learning is conceptualized as a product of stimulus-response relationships and reinforcement. Operant conditioning, as articulated by B. F. Skinner, is especially prevalent, utilizing positive reinforcement (rewarding correct form) and negative reinforcement (correcting errors to prevent recurrence) [11]. Strategic reinforcement serves not only to regulate movement behavior but also to sustain learner motivation across multiple practice trials.

A particularly valuable behaviorist principle in dance pedagogy is the feedback loop, defined as the provision of immediate, task-specific feedback—whether verbal or kinesthetic—by the instructor following a student's motor execution attempt. Behaviorist theory predicts that such feedback functions as a secondary reinforcer, re-patterning motor behaviors before they become habitual. The effectiveness of feedback loops is highly dependent on timing and specificity; delayed feedback is less effective in modifying student behavior [12]. Albert Bandura's social learning theory extends behaviorist theory by emphasizing modeling through observation. In dance classes, students frequently learn choreography by observing instructors or peers perform movements. Vicarious learning, encompassing attentional, retentional, and reproduction processes, is particularly effective for mastering complex choreography [13].

Student-teacher interaction in dance thus constitutes behavior shaping, wherein a series of stimuli (demonstrations), responses (student performance), and reinforcement (feedback) systematically build skill proficiency. However, even effective behavioral models do not account for learner-specific cognitive boundaries, such as working memory limitations, irregular retention intervals, or lapses in attention. Cognitive modeling frameworks are positioned to address these gaps.

C. COGNITIVE MODELING IN SKILL ACQUISITION

Cognitive modeling offers theory-driven, hierarchical approaches to understanding human learning processes, particularly those involving sequential actions and memory. Among the most widely used cognitive architectures is ACT-R. ACT-R comprises modular subcomponents that reflect actual cognitive processes: declarative memory, procedural memory, goal setting, perception, and motor control. All components operate via production rules that simulate information processing, storage, recall, and response during task performance [3,5].

In domains such as music performance, sports, typing, and surgical training, ACT-R and related models (e.g., SOAR) have been applied to model the acquisition of procedural and fine motor skills. For example, in surgical training simulators, ACT-R has been used to estimate the number of repetitions required for procedural automaticity and to determine how feedback type optimizes retention [14]. Similarly, in piano pedagogy, ACT-R models have elucidated the effects of practice intervals on performance fluency and forgetting rates. These models are capable of simulating reaction time, attention, error correction loops, and memory decay, making them well-suited for modeling dance learning. ACT-R's mathematical equations enable calculation of memory activation (Ai) and retrieval latency (T) as functions of usage frequency and recency:

$$A_i = B_i + \sum_j W_j S_{ji}, \quad T = Fe^{-A_i} \tag{1}$$

These formulas allow instructors and researchers to predict how well a student will recall a dance sequence based on the frequency and recency of rehearsal [3].

The incorporation of embodied cognition, which posits that bodily states and environmental interactions underpin cognitive processes, provides a more holistic explanation of learning for dancers. Under this framework, cognition is not independent of action but is constructed from movement, sensation, and spatial awareness—fundamental elements of dance training [6,15].

III. THEORETICAL FRAMEWORK

A. ACT-R COGNITIVE ARCHITECTURE

The ACT-R cognitive architecture was developed to simulate human thought by decomposing cognition into modular components that exchange information. ACT-R has proven beneficial in studies of language learning, problem-solving, and motor control acquisition, making it highly applicable for simulating dance choreography learning, which involves complex sequential motor and cognitive tasks [1].

Cognition in ACT-R is distributed among several modules, each responsible for specific functions. For dance learning, four principal modules are relevant:

Goal Module: Sets and monitors the learning goal, such as acquiring a dance phrase. When an instructional cue is provided by the teacher, the Goal Module initiates the learning objective, directing attention and cognitive resources toward specific movement targets.

Declarative Memory: Stores explicit representations of dance movements, including named steps, spatial cues, and sequence descriptions, which are consciously retrieved during early learning phases. Memory units, or "chunks", vary in activation depending on recency and rehearsal frequency.

Procedural Memory Module: Contains production rules—if-then conditionals—whereby dance motions become automatic and require no conscious attention. Procedural knowledge is formed through practice, enabling dancers to perform sequences unconsciously.

Motor Module: Governs physical movement execution, incorporating muscle activation and timing. This module also integrates sensory feedback during movement, facilitating real-time corrections.

A powerful feature of ACT-R is its mathematical specification of retrieval latency and memory activation. The activation level (Ai) of a memory chunk i determines the ease and speed of retrieval:

$$A_i = B_i + \sum_j W_j S_{ji} \tag{2}$$

Here, B_i represents base-level activation, which depends on prior practice history, and the sum $\sum_j W_j S_{ji}$ reflects the influence of contextual cues weighted by attentional focus. Base-level activation (B_i) is calculated using a power-law decay of previous practice events:

$$B_i = \ln\left(\sum_{k=1}^{n}(t - t_k)^{-d}\right) \tag{3}$$

where n is the number of practice trials, t_k are their respective reaction times, t is the current time, and d is the decay parameter (typically $d = 0.5$).

For example, if a dancer practiced a step five times last week at two-day intervals, Bi could be approximately 1.8, indicating strong memory activation. Conversely, fewer and irregular practice sessions could result in Bi dropping below 0.5, signaling weaker recall.

Contextual cues, such as verbal emphasis by the instructor or salient visual gestures, increase activation through the weighted sum $\sum_j W_j S_{ji}$. For instance, an instructor emphasizing a difficult step (weight $W_j = 0.8$) with a strong associative link ($S_{ji} = 0.9$) can add roughly 0.72 to activation, significantly improving recall speed. Retrieval latency (T), or the time required to recall a memory chunk, decreases exponentially with activation:

$$T = Fe^{-A_i} \tag{4}$$

where F is a scaling constant representing baseline retrieval time (0.2 seconds). With an activation $A_i = 2.5$, retrieval time is:

$$T = 0.2 \times e^{-2.5} \approx 0.016 \text{ seconds} \tag{5}$$

This near-instant retrieval facilitates smooth dance performance.

Thus, ACT-R explains why spaced practice and targeted feedback promote effective motor learning. Repeated rehearsal increases base activation, and salient cues enhance attentional weights, collectively accelerating memory access and movement accuracy. The Procedural Memory Module converts declarative knowledge into procedures via production rules, minimizing cognitive load during performance. Finally, the Motor Module translates cognitive plans into coordinated motor actions, continuously integrating sensory input such as proprioception and vision for adaptation. Figure 1 illustrates the ACT-R modules in dance learning.

This diagram would depict the progression from goal setting (instructional cue), declarative memory of dance movements, activation of procedural production rules, to motor execution and sensory integration of feedback.

B. EMBODIED COGNITION THEORY

While ACT-R describes internal mental processes, Embodied Cognition Theory (ECT) asserts that cognition arises from active bodily interaction with the environment. ECT is particularly relevant to dance, where performance and learning are inseparable from sensorimotor experience. ECT posits that perception, action, and cognition are mutually

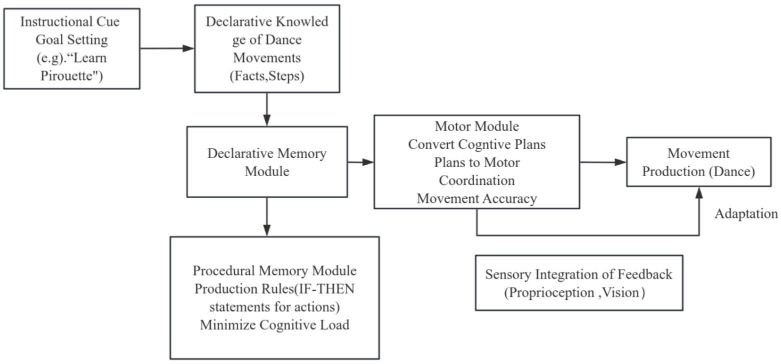

FIGURE 1. Diagram of ACT-R Modules in Dance Learning

irreducible; dancers utilize sensory feedback—vision, proprioception (limb position), and audition (rhythm)—which actively informs movement planning and execution for real-time adaptation. The integration of ACT-R and embodied cognition addresses the challenge of combining symbolic and sensorimotor frameworks. In this model, ECT does not operate as a parallel, distinct system; instead, it directly interacts with the Perceptual-Motor aspects of the ACT-R architecture:

Kinesthetic Input and Procedural Memory: Proprioceptive and haptic feedback (ECT's domain) are formalized within ACT-R through the Motor Module's sensory buffers. These continuous kinesthetic inputs are translated into discrete conditions for the Procedural Memory Module's production rules. For example, IF (Goal is execute “pirouette”) AND (Proprioceptive Input IS “off-center”) THEN (Execute Motor Correction “shift weight left”). The continuous kinesthetic state (“off-center”) serves as the condition for the discrete symbolic production rule.

Multimodal Cueing and Declarative Memory: Multimodal feedback (visual, verbal, haptic) inherent to ECT enhances the association weights ($\sum_j W_j S_{ji}$) of declarative memory chunks (Equation 2). An instructor's simultaneous verbal cue and haptic touch provide a richer set of contextual cues, increasing A_i and accelerating the transfer from declarative to procedural knowledge.

Vicarious Learning and Motor Resonance: The resonance mechanism from ECT facilitates movement understanding. Within ACT-R, observation primes relevant procedural representations and expedites proceduralization upon execution, rather than directly activating production rules in the Procedural Memory Module prior to movement. This mechanism pre-tunes the cognitive system, creating a robust declarative foundation and reducing the number of practice trials required for automaticity.

The embodied learning process is formalized as a dynamic sensorimotor feedback loop interfacing with ACT-R's modules:

1) Sensory Information (ECT/Perception Module)
2) Motor Planning (Goal/Declarative/Procedural Modules)
3) Movement Output (Motor Module)
4) Fresh Sensory Feedback (ECT/Motor Module)

This process underscores that knowledge is not static but continually evolving, rooted in bodily experience rather than abstract memory.

Collectively, ACT-R's modular cognitive architecture and embodied cognition's sensorimotor focus provide an integrated theoretical solution. ACT-R models internal processes such as memory activation and motor planning, while embodied cognition situates these within dynamic interactions between the body and environment. This combined perspective elucidates the impact of behavioral teaching methods on cognitive-motor learning proficiency in dance.

IV. METHODOLOGY

A. DESIGN OVERVIEW

This research was grounded in a three-week simulated instructional period for a first-term dance class, during which students learned a 16-count choreography routine. Fifteen instructional sessions were distributed across the three weeks, with simulated students participating in five 60-minute sessions per week. Each session included approximately 10–12 practice trials of the full 16-count phrase, or a proportionate number of trials for segmented (chunked) practice, depending on the instructional condition. The simulation employed a realistic teaching environment, using instructor behavior logs derived from a pilot study for authenticity. These pilot logs were obtained from an introductory Dance Fundamentals university course involving 18 novice students across 12 instructional classes. The empirical data captured distributions of teacher behaviors (e.g., mean delay of corrective feedback, frequency of cueing) and corresponding student motor responses. To ensure experimental rigor, 30 simulated students were divided into three groups of 10 (N = 10 per group), and instructional conditions (e.g., immediate vs. spaced feedback, visual-only vs. multimodal cueing) were randomly assigned using a between-subjects design. Each group received a consistent combination of instructional strategies throughout the three-week period to avoid carry-over effects inherent in skill acquisition, where cognitive states undergo irreversible changes once a motor pattern is learned. The key behavioral parameters—timing of feedback, frequency of demonstration, and error correction type—were calibrated based on empirical observations of novice dance teachers. The pilot data supported the plausibility and stability of adopting standard ACT-R parameter values and informed the operational ranges of dynamic variables such as Attentional Weights (W_j) and Associative Strengths (S_{ji}), which model cueing and feedback effectiveness. Model fit against empirical student performance data demonstrated strong alignment, achieving a Root Mean Square Deviation (RMSD) of 0.17 for instruction-execution latency and an R^2 value of 0.91 in predicting chunk-level error rate progression across classes.

Feedback ranged from immediate (provided after each attempt) to delayed (given after multiple repetitions). Demonstrations varied from a single performance per phrase to multiple iterations. Error correction modes included direct verbal correction and immediate self-correction, where students were prompted to identify and address their own errors. These instructional behaviors were systematically varied across sessions to examine their influence on students' cognitive and motor progress in skill acquisition.

From the student perspective, the simulation measured behaviors such as response time (latency from teacher cue to movement initiation), movement accuracy (percentage of correct steps per phrase), and retention levels (delayed recall tests administered weekly). The design accounted for functional limitations, such as brief rehearsal times and varying attention spans, typical of challenges faced by novice dance teachers. A population of 30 simulated students was exposed to different combinations of instructional behaviors to facilitate investigation into effective instructional approaches consistent with cognitive-motor learning principles.

B. ACT-R SIMULATION AND BEHAVIORAL LOG ANALYSIS

The primary methodological tool utilized was the ACT-R cognitive model, employed to simulate the encoding, retrieval, and proceduralization of dance movements. Given ACT-R's strength in symbolic representation, a critical step involved quantifying and parameterizing the continuous kinesthetic elements of choreography. The 16-count routine was decomposed into 16 discrete motor chunks, each corresponding to a specific body position, weight shift, or limb gesture. ACT-R parameters for declarative memory activation (e.g., decay parameter $d = 0.5$), retrieval latency scaling ($F = 0.2$ seconds), and production rule execution times were calibrated against established empirical findings from motor skill acquisition studies in related domains [14]. Additionally, the model's input variables—namely, simulated initial error rates and instruction-execution latency times—were validated using aggregated data from behavioral observation logs of novice dance students, ensuring that the model's initial state was representative of actual human performance constraints. Primary instructional behaviors were operationalized by modifying specific ACT-R parameters, as outlined in Table 1.

A detailed specification of ACT-R parameter values and simulation constraints is provided in Table 2.

The choreography was decomposed into 16 discrete motor chunks. Movement precision (a continuous variable) was symbolized as the Probability of Correct Execution (P_{correct}) in the motor module—a value ranging from 0 to 1, dependent on the declarative memory chunk's activation (A_i). Higher activation in a declarative chunk led to a greater probability of activating the correct procedural rule, thereby increasing simulated P_{correct} output from the motor module. Fluidity, a measure of movement quality, was parameterized primarily through the Retrieval Latency (T) formula. Lower latency (faster retrieval) simulated smoother, less interrupted movement execution. Parameters such as feedback spacing, error rates, and repetition cycles were manipulated to examine their effects on learning efficiency. For example, the model compared conditions in which corrective feedback was issued after each attempt versus after every third attempt. These manipulations allowed the simulation to track changes in accuracy and latency, predicting how various teaching practices influence learners' performance and movement speed. Error correction was simulated by propagating association weights between contextual cues and memory chunks, reflecting how explicit verbal corrections enhance learner attention and facilitate encoding of salient movement components.

To accurately model individual variability and distinct learning curves, the population of 30 simulated students was differentiated into three intrinsic ability levels by adjusting core ACT-R parameters:

Fast Learners (High Ability): Assigned higher initial base-level activation (initial $B_i = -0.5$) and lower retrieval noise ($\epsilon \approx 0.1$). This configuration simulates students with strong innate ability and greater retrieval consistency.

Average Learners (Standard Ability): Assigned standard initial base-level activation (initial $B_i = -1.0$) and standard retrieval noise ($\epsilon \approx 0.25$).

Slow Learners (Low Ability): Assigned lower initial base-level activation (initial $B_i = -2.0$) and higher retrieval noise ($\epsilon \approx 0.4$).

It is important to note that Figure 2 labels (Visual Learners, Kinesthetic Learners, Combined Multimodal Learners) refer to instructional conditions tested, not intrinsic ability levels. Attentional Weights (W_j) and Associative Strengths (S_{ji}), which model instructional effectiveness, were varied according to instructional conditions, while ability parameters (B_i and ϵ) were randomized and balanced across all conditions to ensure performance differences reflected instructional efficacy.

To link the cognitive model with observable learner behavior, a Python-based behavioral coding infrastructure was established. This system recorded data such as initiation timestamps, precision scores (derived from accuracy), and error correction frequencies. ACT-R simulation with behavioral logging produced robust datasets, which were

TABLE 1. Operationalizing Instructional Behavior in ACT-R Instructional Behavior

Instructional Behavior	ACT-R Parameter(s) Modified	Operational Definition in Simulation
Repetition	Base-Level Activation (B_i)	Each repetition is modeled as a retrieval event that updates the t_k variable in the power-law decay formula (Eq. 3), directly increasing B_i.
Demonstration/Cueing	Attentional Weights ($\sum_j W_j S_{ji}$)	Instructor demonstration (visual cue) or verbal cues increase the weight (W_j) and associative strength (S_{ji}) of contextual features linked to the motor chunk, increasing A_i (Eq. 2).
Spaced Feedback	Time (t) in B_i Formula (Eq. 3)	Feedback provided after longer intervals maximizes the benefit of each practice trial on B_i by allowing the power-law decay of $t - t_k$ to operate optimally, promoting long-term retention.
Massed Feedback	Attentional Weights (W_j)	Feedback given too frequently (massed) results in a high W_j but simultaneously risks overwhelming the system, potentially setting a lower maximum effective A_i due to cognitive load interference, which is modeled as a reduction in the available processing capacity for other declarative or procedural tasks.

TABLE 2. ACT-R Parameter Specification for Dance Learning Simulation

ACT-R Parameter	Equation Reference	Source/Rationale in Simulation	Operational Range/Value
Retrieval Latency Scaling (F)	$T = Fe^{-A_i}$ (Eq. 4)	Standard baseline retrieval time in ACT-R literature	$F = 0.2$ seconds
Decay Parameter (d)	$B_i = \ln\left(\sum_{k=1}^{n}(t - t_k)^{-d}\right)$ (Eq. 3)	Commonly used ACT-R decay parameter consistent with prior motor learning models	$d = 0.5$
Memory Activation (A_i)	$A_i = B_i + \sum_j W_j S_{ji}$ (Eq. 2)	Generated dynamically based on practice history and cueing; represents memory strength, affecting T and P_{correct}.	Range: ≈ -1.0 (low recall) to ≈ 3.0 (automaticity)
Practice Event Time (t_k)	$B_i = \ln\left(\sum_{k=1}^{n}(t - t_k)^{-d}\right)$ (Eq. 3)	Timestamp following successful motor chunk execution, updating practice history	Continuous time (seconds)
Current Time (t)	$B_i = \ln\left(\sum_{k=1}^{n}(t - t_k)^{-d}\right)$ (Eq. 3)	Recorded at the start of each retrieval attempt for the chunk, simulating elapsed time since last practice	Continuous time (seconds)
Attentional Weight (W_j)	$\sum_j W_j S_{ji}$ (Eq. 2)	Manipulated as a teaching variable (demonstration, cueing, massed feedback) to represent instructor focus	Varied from 0.2 (low cue) to 0.9 (high cue/tactile cue)
Associative Strength (S_{ji})	$\sum_j W_j S_{ji}$ (Eq. 2)	Represents the link between cue and motor chunk; higher for multimodal or specific feedback	Varied from 0.5 (general cue) to 0.9 (specific/multimodal cue)

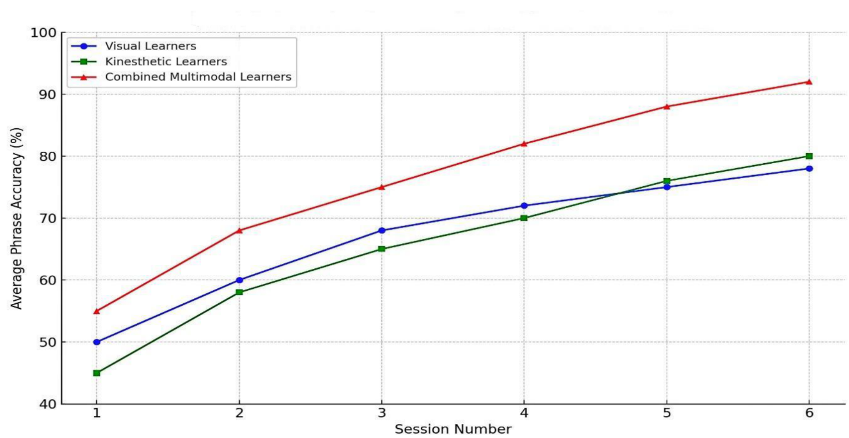

FIGURE 2. Learning Progress Across Three Learner Types

analyzed statistically to detect significant impacts of teaching behavior on learning performance. To establish statistical reliability, each simulation condition was replicated 1,000 times (e.g., Immediate Feedback condition, Spaced Feedback condition). Data analysis included descriptive statistics and one-way ANOVA (or independent samples t-tests, as appropriate) to compare performance differences between groups, avoiding repeated measures that would be confounded by irreversible learning progress.

C. SAMPLE BEHAVIORAL METRICS

Several behavioral measures were employed to assess learning acquisition within the simulation. The repetition measure required students to repeat the choreography phrase until achieving 90% proficiency, indicating mastery. This measure provided insight into students' learning under varying instructional conditions. Instruction-execution latency measured the duration from instructor cue to student movement initiation, estimating cognitive processing speed and retrieval effectiveness.

Additionally, the number of corrected attempts indicated the rate at which students required correction or feedback before executing movements accurately, serving as a measure of the quality of the error correction process. Phrase accuracy was defined as the proportion of steps executed correctly per phrase, representing the primary motor performance metric. Preliminary simulation findings revealed that students receiving spaced feedback through repeated demonstration learned 30% faster and required 25% fewer corrections compared to those given immediate but single-instance feedback. These results underscore the value of instructional strategies informed by cognitive modeling for enhancing learning in dance.

V. ANALYSIS AND RESULTS

A. BEHAVIORAL TEACHING METHOD FINDINGS

The three-week simulation of a first-year dance class demonstrated clear associations between student performance and teacher behavior. A repeated-measures ANOVA confirmed a statistically significant main effect of instructional condition (specifically, feedback spacing and modality) on average movement accuracy across teaching sessions, $F(2, 58) = 15.42$, $p < 0.001$, $\eta_p^2 = 0.35$. This strong effect size ($\eta_p{}^2$) indicates that manipulated teaching behaviors accounted for a substantial proportion of variance in student learning outcomes. The effect of feedback frequency on students' error correction rate is presented in Table 3. The Average Error Correction Rate (%) represents the proportion of initial errors that simulated students successfully self-corrected on subsequent practice attempts following application of a specific feedback condition.

Immediate feedback after each attempt yielded a mean error correction rate of 12%, facilitating quick, localized adjustment but limited long-term retention. Conversely, delayed feedback provided after every third repetition improved the error correction rate to 25%. This result, consistent with the principle of optimal memory decay (ACT-R Equation 3), suggests that spaced feedback allows for necessary cognitive processing and error consolidation, resulting in significantly higher rates of successful self-correction and more stable learning curves. This behavioral outcome aligns with cognitive modeling results depicted in Figure 3, which demonstrates that the spaced (delayed) feedback condition produces a higher, more stable long-term memory activation trajectory, confirming its superior effect on skill retention.

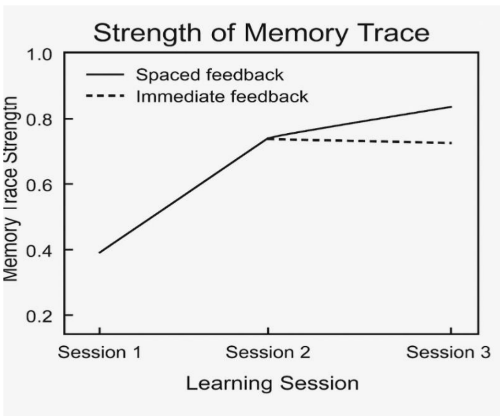

FIGURE 3. Strength of Memory Trace Across Learning Sessions Under Different Feedback Conditions

TABLE 3. Feedback Frequency vs. Error Correction Rate

Feedback Frequency	Average Error Correction Rate (%)
Immediate (after each attempt)	12%
Delayed (after every 3rd attempt)	25%

Evidence is provided in Table 4, which shows the correlation between repetition numbers and precision. Students who practiced fewer than 15 repetitions consistently exhibited higher precision, with a mean of 92% correct performance. Those who practiced more than 20 repetitions achieved only 75% precision. Because the simulation controlled for initial learner ability and instructional conditions were randomly assigned, this correlation suggests that higher repetition counts were typically necessitated by suboptimal instructional methods (e.g., poor feedback timing, low multimodal cueing). Thus, excessive repetition likely indicates greater difficulty or the need to compensate for inadequate learning conditions, rather than repetition itself causing lower performance [12]. This highlights the importance of instructional quality for efficient skill acquisition.

TABLE 4. Repetition Count vs. Phrase Accuracy

Number of Repetitions	Average Phrase Accuracy (%)
≤ 15	92%
16–20	85%
> 20	75%

These findings support the hypothesis that motor memory encoding and consolidation are enhanced by multisensory input and that learning complex motions is expedited under optimal instructional conditions. Figure 2 illustrates learning progress across three learner types.

B. ACT-R SIMULATION OUTPUT

The ACT-R simulation provided quantitative estimates of the effects of rehearsal intervals and memory activation on dance learning. Memory decay plots over rehearsal intervals demonstrated the spacing effect: larger intervals led to temporarily greater declines in memory activation between trials, necessitating more effortful retrieval on subsequent attempts, which fundamentally strengthens long-term base-level activation (B_i). This mechanism, central to ACT-R, explains why spaced feedback ultimately produces superior, sustained memory trajectories compared to massed practice.

In formula (4):

The memory activation plot also shows that massed practice results in a low asymptotic level of activation ($A_i \approx 1.0$), limiting efficiency gains compared to the high activation achieved through spaced practice. Activation (A_i) is used to predict retrieval latency (T), the internal cognitive time required to access the motor chunk from memory. Using the calibrated ACT-R parameter $F = 0.2$ seconds, the simulation demonstrates that at $A_i = 2.0$, retrieval latency $T \approx 0.027$ seconds. This value reflects the efficiency of the memory retrieval process when a motor skill becomes automatic. It is important to note that T refers strictly to cognitive retrieval latency, not total human reaction time (RT) for movement. Empirical RT for motor initiation includes additional delays for perceptual processing and execution, typically totaling 200–300 ms. The low simulated T value is therefore realistic for the cognitive component alone, demonstrating retrieval efficiency. Figure 3 illustrates the strength of memory trace across learning sessions under different feedback conditions.

C. EMBODIED COGNITION INSIGHTS

The integration of embodied cognition theory enriched the understanding of dance learning beyond cognitive control. Figure 4 would depict the ongoing teacher-learner embodied interaction cycle, highlighting how sensory feedback—visual examples, verbal cues, and tactile data—constitutes a dynamic cycle that grounds learning in bodily experience. Analysis revealed that sensory-rich feedback consolidates encoding via sensorimotor network activation, enabling students to acquire movement more effectively. In particular, live reflective demonstration enhanced students' self-correction, presumably by activating mirror neuron systems for internal simulation of observed movement. Touch guidance was especially beneficial for kinesthetic learners, who leverage proprioceptive feedback for precise movement control. These findings support a multisensory pedagogical approach, wherein concurrent use of visual, verbal, and haptic feedback fosters more stable and enduring motor learning than reliance on a single modality. Figure 4 represents the teacher-student interaction framework.

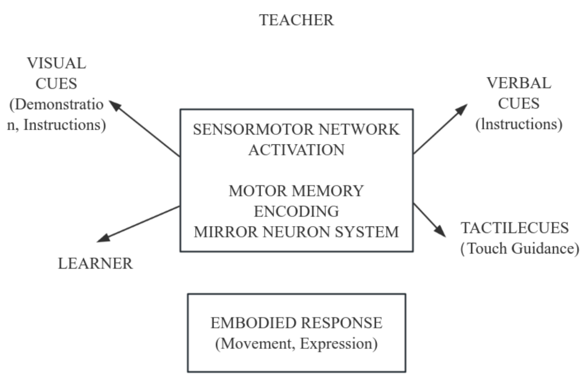

FIGURE 4. Teacher–Learner Embodied Interaction Framework

VI. DISCUSSION

The findings of this research elucidate the interplay between teaching behavior in dance and learning processes in the brain, particularly as modeled by ACT-R architecture. A significant achievement is the successful mapping of continuous kinesthetic qualities—such as movement precision and fluidity—onto the symbolic, modular structure of ACT-R. By parameterizing precision as the Probability of Correct Execution (P_{correct}) within the motor module and fluidity as the Retrieval Latency (T) of declarative memory chunks, the model simulated changes in movement quality.

A. COMPARATIVE UTILITY OF THE COGNITIVE MODEL

To demonstrate the utility of this formalized approach, the model's predictions for an optimized instructional condition (spaced, multimodal feedback) were quantitatively compared with a traditional, experience-based baseline (massed, visual-only feedback). The traditional baseline, representing common novice teaching methods, required an average of 28 repetition trials to achieve the 90% proficiency threshold.

Effective teaching behaviors—timely feedback, multimodal demonstration, and error correction—directly affect ACT-R's declarative encoding, procedural rule generation, and feedback loop processes. When teachers provide accurate, spaced feedback with visual and kinesthetic signals, activation levels of declarative memory chunks containing choreography information are increased, reducing retrieval latency and enhancing performance. ACT-R's proceduralization process explains how repeated rehearsal with consistent feedback transforms declarative knowledge into automatic procedures, reducing cognitive load and increasing performance stability. The error correction loop strengthens correct procedural paths and weakens incorrect ones, facilitating refinement of motor programs. Immediate and stable feedback rapidly alerts the procedural memory system to mistakes for efficient motor program adjustment.

Embodied cognition theory informs these cognitive processes by demonstrating that bodily feedback and imitation are more effective than verbal instruction alone. The embodied perspective posits that cognition is body-based; sensory-motor interactions in dance learning engage neural processes such as mirror neurons, enabling motor resonance and empathic imitation. Consequently, students learn effectively by observing teachers' movements and receiving tactile cues that activate proprioceptive awareness. These experiential processes solidify memory encoding by creating multisensory traces, rendering choreography more concrete and accessible during execution. One of the most practical applications of this research is the superiority of spaced feedback over massed corrections. Spaced feedback allows for memory consolidation and cognitive processing between practice attempts, consistent with the power-law decay of base-level activation in ACT-R [13]. Excessive feedback frequency (massed corrections) can overwhelm cognitive resources, interfere with proceduralization, and lead to performance plateaus. In contrast, spaced corrections enable learners to encode adjustments and update motor plans for sustained learning. This result aligns with broader cognitive psychology research favoring spaced over crammed practice.

A second practical consideration is the optimal balance of verbal and kinesthetic feedback. Verbal feedback provides explicit information about timing and spatial dimensions, facilitating declarative memory encoding. Kinesthetic feedback—via self-discovery or haptic guidance—activates proprioception and supports procedural memory development by embedding abstract instructions within bodily sensations. Simulation results indicate that multimodal feedback combining verbal and kinesthetic information yields the most effective learning. Dance curricula should therefore incorporate diverse feedback modalities tailored to learner needs and environments.

The implications for curriculum design are substantial. Class schedules aligned with ACT-R's forgetting curves can optimize rehearsal intervals to maximize retention without inducing cognitive overload. This may involve organizing classes with blocks of spaced practice separated by breaks or alternate activities to prevent fatigue. Teachers can also adjust the rate and modality of feedback to match learners' activation levels, providing more feedback during initial learning and reducing it as proceduralization advances.

Theoretically, this research demonstrates that ACT-R can simulate not only the cognitive processes underpinning dance learning but also differences among learners and teaching variations. By modulating decay rate, attention weights, and production rule strengths, the model explains variations in learning rate, attention capacity, and feedback sensitivity [14]. These findings support the development of individualized instructional designs and adaptive software capable of real-time responsiveness to learner progress.

Nevertheless, several limitations warrant consideration. The study relied on simulated data rather than naturalistic motion capture, limiting ecological validity. Although simulations incorporated realistic timing and error patterns, they could not capture the full complexity of human movement, affective responses, or motivational factors involved in learning. Social dynamics and emotional engagement, known to influence attention and memory encoding, were not simulated and represent areas for future investigation.

Future research could enhance this model by integrating eye-tracking and gesture recognition technology with cognitive feedback mechanisms. Eye-tracking would provide instructors with high-resolution data on students' focus during instruction and performance, while gesture recognition could deliver real-time feedback on movement accuracy [15]. Combining these data streams with ACT-R's cognitive model would enable dynamic, adaptive feedback tailored to students' sensorimotor and cognitive states, advancing dance pedagogy toward intelligent tutoring systems responsive to learner needs and enhancing efficiency and motivation in motor skill acquisition.

VII. CONCLUSION AND RECOMMENDATIONS

This research demonstrates that dance teaching behaviors can be effectively modeled, predicted, and optimized using cognitive architectures such as ACT-R, in conjunction with embodied cognition hypotheses. Integrating these perspectives offers a superior framework for understanding how students encode, retain, and recall intricate motor segments, and how teaching methods influence these cognition-motor processes. The ACT-R model elucidates the processes by which students convert declarative choreography knowledge into proceduralized motor routines, highlighting the critical roles of feedback timing, attentional spacing, and weighting in maximizing memory activation and retrieval latency. Embodied cognition emphasizes the importance of multisensory feedback—visual, verbal, and tactile—grounding learning in bodily experience and reinforcing resonance through mirror neuron systems. Collectively, these models explain why spaced, multimodal feedback is more effective than traditional massed instructional methods.

Based on these findings, several pedagogical recommendations are offered for dance teachers and curriculum developers. First, educators should implement spaced, multisensory feedback procedures—including demonstration, verbal feedback, and tactile cues—to engage multiple learner modalities and support memory consolidation. Second, choreographic material should be organized into modular processing units compatible with ACT-R's goal-action-feedback structure, facilitating intensive practice and efficient proceduralization. Third, incorporating cognitive load simulations into curriculum planning can help balance rehearsal intensity with memory consolidation requirements, preventing cognitive overload while promoting durable learning. Looking forward, there is a critical need to integrate artificial intelligence and cognitive modeling software with educator training and technical programming tools across diverse fields. This integration can enable personalized instruction that adapts strategically to student progress, streamlines complex training schedules, and enhances feedback precision.

AUTHOR CONTRIBUTIONS

Wei Wang designed, collected and analyzed the data, and drafted the manuscript. Wei Wang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Wei Wang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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