

Breaking it Down: Expertise and Dance Segmentation

R. Lane Adams (radams29@uic.edu)

Department of Psychology, University of Illinois at Chicago
Chicago, IL 60607 USA

Jennifer Wiley (jwiley@uic.edu)

Department of Psychology, University of Illinois at Chicago
Chicago, IL 60607 USA

Abstract

This study investigates how expertise influences the mental representation of dance choreography, focusing on differences between expert and novice ballet dancers. Event Segmentation Theory (EST) was used to examine chunking in a 50-step ballet sequence. Participants, classified as experts or novices based on dance experience, were tasked with segmenting choreography across repeated viewings. Results showed that experts segmented the sequence into fewer, larger chunks, and showed greater consistency and greater similarity with each other. Novices, in contrast, identified more segments and showed less agreement. These findings underscore the role of domain-specific knowledge that incorporates the structure of the domain in forming mental representations, and sets the stage for exploring how this may enable superior expert learning and memory for very long sequences of dance.

Keywords: expertise; event segmentation; chunking; dance memory

Introduction

For most people, reproducing a dance seen only once on stage would be a significant challenge, but for a professional dancer, learning a 96-step dance routine after one viewing is a manageable feat (Allard & Starkes, 1991). In contrast to novices who experience typical limitations in short-term memory (Cowan, 2001; Miller, 1956) and struggle to retain new sequences of information, experts exhibit remarkable memory capabilities, easily recalling vast amounts of domain-specific information even after brief exposures (Ericsson, 2018; Ericsson & Delaney, 1998; Ericsson & Kintsch, 1995). For instance, chess masters can recreate multiple chessboards with precision after viewing each for just a few seconds (Gobet & Simon, 1996b). Similarly, experienced actors have been found to recall scripts more efficiently (Noice & Noice, 2006) and those with poetry experience can remember lengthy ballads with greater ease (Rubin et al., 1993). These exceptional abilities result not from a fundamentally different memory system but from the effective use of long-term memory through the recognition of familiar patterns and other strategies (Adams & Delaney, 2023; Ericsson & Kintsch, 1995; Gobet & Simon, 1996b).

Theories of expert memory emphasize two essential principles: the ability to recognize patterns and the ability to encode and retrieve those patterns effectively. Through repeated exposure to domain-specific patterns experts develop a large, easily accessible knowledge base, and skills

that allow them to identify critical elements, integrate new information with prior knowledge, create retrieval strategies, and minimize memory interference—an issue often associated with forgetting (Adams & Delaney, 2023). Some of the earliest evidence of superior memory in experts comes from research on chess players. In a 1927 study, Soviet psychologists tested chess masters' recall of random chess positions during a Moscow chess tournament. Their results showed that chess masters outperformed non-experts in episodic memory tasks involving game positions but displayed no advantage in non-chess-related memory tasks, highlighting the specificity of benefits from expertise (Vicente & de Groot, 1990). Later studies, such as those by de Groot (1965) and Chase and Simon (1973), confirmed these findings, demonstrating that chess masters could recall realistic chess configurations with high accuracy after minimal exposure, but struggled (at least initially) with arrangements that did not follow the rules of chess. These findings illustrate how expert memory leverages meaningful patterns stored in long-term memory (Charness, 1976), or said another way, how semantic memory can be used to support episodic memory.

The concept of "chunking", first introduced by Miller (1956), explains how information is organized into meaningful units to enhance episodic memory. Short-term memory is able to manage only a limited amount of information (about 7 ± 2 chunks, now thought to be only 4, Cowan, 2001), but with practice, these units can grow in complexity, enabling experts to store and retrieve more extensive information structures. For chess masters, the ability to rapidly reconstruct board positions reflects this integration of chunking and long-term memory (Chase & Simon, 1973; de Groot, 1965). Chase and Simon proposed that chess masters use "chunks", or semantic groupings of related pieces, encoded in short-term memory with cues stored in long-term memory for retrieval. Computer modeling estimated that the expert performance of chess Grandmasters involves roughly 50,000 chunks stored in memory (Gobet & Simon, 1996a; Simon & Gilmarin, 1973). This framework explains how experts can make quick decisions in familiar contexts while systematically exploring unfamiliar ones. Subsequent models like template theory (Gobet & Simon, 1996b, 1998) refined this understanding by positing that advanced chunks form templates—units with fixed core elements and flexible slots for variable

information. These templates enable experts to organize, encode, and retrieve information efficiently.

A further feature of domain-related knowledge in long-term memory is that it is well-organized. That is, it appears to be meaningfully organized in relation to the structure of the domain. Chi et al. (1981) found that physics experts solve problems differently from novices. Experts relied on well-developed schemas that enabled them to categorize problems based on deep structural features, such as fundamental physics principles, whereas novices focused on surface-level characteristics. This hierarchical organization of knowledge allows experts to approach problems more efficiently by quickly identifying key components and applying the appropriate solution strategies.

Similar evidence about the organization of expert memory was later found in Chi et al. (1989), which assessed how children structure and use knowledge about dinosaurs. When asked to categorize dinosaurs, higher knowledge participants were more likely to sort based on meaningful features rather than surface similarities. For instance, expert children sorted dinosaurs into taxonomic families and broader categories like plant-eaters and meat-eaters, whereas novices used more superficial, idiosyncratic groupings. When asked to reason about new examples, the experts were able to access relevant concepts in memory, used more causal and comparative reasoning, and drew connections between related concepts, which allowed them to make accurate inferences about novel instances. These results suggest that superior cognitive performance from experts is a result of memory representations that are structured around core domain principles rather than isolated facts. The observation that expert chunks are similar to each other is consistent with the assumption that these structures in memory arise from experience to reflect the fundamental principles in the domain.

Expertise and Dance Memory

Similar to the findings from chess experts, studies on expert dancers have found superior memory for dance sequences compared to novices (Deakin & Allard, 1991; Poon & Rodgers, 2000; Smyth & Pendelton, 1994; Starkes et al., 1990). Although most of these studies employed relatively short dance sequences, a recent study found that ballet experts were able to learn most of the steps in a 50-step dance after only 5 viewings (Adams et al., 2023). In comparison, novices recalled far fewer moves after the first exposure, more similar to typical limits of short-term memory. Further novices showed modest gains from additional viewings while experts showed learning at a significantly faster rate. An overarching goal motivating the present work is explore other differences between experts and novices that could be used in future studies to understand how dance experts are able to learn lengthy new dance sequences so effectively, and how they are able to circumvent the normal limits of short-term memory.

Adams et al. (2023) suggested that dance experts, like other experts, leverage semantic memory to process and learn large

amounts of new information efficiently. In dance, experts may possess prior knowledge that helps them to predict the probability of a step within a sequence of moves. For instance, in ballet, an expert dancer understands that a "tombé" is often followed by a "pas de bourrée". This knowledge of likely transitions between steps allows the expert to form coherent structures from sequences that might seem unrelated to novices. Such structuring facilitates memory by grouping elements into functional units, or chunks, making it easier to learn, retain, and execute choreography.

In contrast to chess, where the goal is to win the game, and expert memory emerges as a byproduct (Gobet & Simon, 1996b), in dance, memorizing the sequence is the primary goal. Consequently, much of the memory research in dance has focused on the specialized learning strategies and adaptive approaches that have been developed to learn specific choreography (Bassetti, 2014; Kirsh, 2011; Kirsh et al., 2009; Saura & Kirsh, 2010; Stevens et al., 2019). In one early study using interviews, Poon and Rodgers (2000) found significant differences between how experts and novices described the strategies they used to learn choreographies. Experts employed verbal labels to group steps into fewer, larger chunks, often agreeing on the partitions within the choreography. In contrast, novices created more fragmented, smaller chunks. Interestingly, when asked how they learned the dance sequences, experts reported practicing chunks individually, while novices often restarted from the beginning of the sequence, highlighting differences in strategy and memory organization. A main purpose of this study was to explore whether evidence for chunking, and consistency across experts in chunking, could be seen using a different methodology, namely an episode-segmenting task inspired by Event Segmentation Theory.

Event Segmentation Theory Because dance involves continuous and dynamic movement, Event Segmentation Theory (EST) offers a valuable framework for understanding expert advantages in memory for dance sequences as episodes or events. According to EST, humans interpret ongoing activity by dividing it into discrete, meaningful events (Zacks & Swallow, 2007). These events are organized through "event models", which are working memory representations that integrate sensory inputs with prior knowledge to predict future actions. In dynamic contexts like dance, segmentation depends on the constant updating of these event models in response to new information. When predictions fail, event boundaries are formed. Experts, because they can integrate movements into cohesive and meaningful units, are likely to perceive fewer segment boundaries.

Similar to chunking in memory theories, EST suggests that segmentation happens automatically during encoding, creating hierarchical structures and units within events. While some prior research has used implicit memory methods to identify musical units (Ongchoco & Scholl, 2020), the current study explicitly asked participants to

indicate segment boundaries to reveal the units or chunks within their event models for dance sequences. Some studies, including those by Bläsing (2015), have already begun using segmenting tasks, and have found that professional dancers and non-dancers differ in their segmentation patterns. Specifically, they have reported that professional dancers perceive fewer segment boundaries, reflecting their ability to process movement sequences as interconnected flows rather than discrete units. In contrast, novice dancers perceived the dance as individual steps. However, segmentation tasks can also allow for testing the degree in which the experts are using the same segments as each other. This aspect of expert memory has not yet been analyzed

Analyzing the similarity of expert chunks is crucial because simply stating that experts form larger chunks than novices does not fully capture the nature of expertise. The consistency in chunking patterns among experts provides insight into the cognitive structures that support their superior memory and performance. Specifically, when experts consistently segment information in the same way, it suggests that they rely on shared schemas and that their long-term memory is organized around the same underlying domain structure. If experts' chunks were merely larger but varied significantly between individuals, it would imply that each expert is using a unique, idiosyncratic strategy rather than a structured, domain-specific system. However, when experts with similar training demonstrate similar chunking patterns, it indicates that they are drawing from the same fundamental schema, reinforcing the idea that expertise is built upon a well-organized and predictable cognitive framework.

Another question in understanding expert memory is how repeated exposure influences the learning and organization of information. Previous studies, such as Bläsing (2015), have demonstrated that segmentation patterns shift after multiple viewings, suggesting that familiarity with a sequence impacts how it is mentally structured. Thus, the number of segments might be expected to decrease for both novices and experts with increased exposure. However, prior findings from Adams et al. (2023), showed that expert dancers learned the choreography at a significantly faster rate than novices. This might suggest that they undergo more changes in their segmentation across viewings. If expert dancers refine their memory representations through repeated exposure, then examining segmentation patterns at multiple time points can provide insight into how their mental organization evolves. After the first viewing, dancers may have a general sense of the choreography, but with repeated exposure, their perception of structure may shift as steps are integrated into a more coherent framework. If expert dancers' increases in memory across viewings are due to improved chunking, then we would expect to see changes in their segmentation patterns that reflect increasing alignment with an organized, schema-driven representation of the choreography. Conversely, if experts are able to chunk efficiently already from the outset, then their number of segments might start low and remain relatively stable across multiple viewings.

The Current Study

The present study seeks to extend prior research by examining how experts and novices chunk ballet sequences through the lens of EST. While Bläsing (2015) used a segmentation task to explore how experts and novices divide dances into units, they did not investigate the extent to which their segmentations align with one another. It is expected that experts will identify fewer segments than novices, reflecting their ability to process movement sequences as interconnected flows rather than discrete units. Additionally, experts are expected to demonstrate a higher degree of agreement regarding the locations of segment boundaries, indicative of shared schematic knowledge that incorporates the structure of the domain.

Method

Participants

Forty-five ($N = 45$) undergraduate students from a large public university in the United States participated in the study. Participants were unpaid volunteers or received course credit as part of an introductory psychology subject pool. Participants self-reported their formal ballet and other dance experience, which was used to classify them as either experts or novices. Experts ($n = 5$) were defined as having at least 10 years of formal ballet training, and novices ($n = 40$) reported no formal dance training.

Materials

A 50-step ballet sequence from Adams et al. (2023) was used; this prior study found that experts demonstrated superior memory after a single viewing, rapid learning, and near mastery after only a few exposures. In contrast to the prior study, participants were not asked to perform the dance in this study. The dance sequence was choreographed and video-recorded by professional dancer and choreographer. The sequence consisted of 50 steps and was approximately one minute in length. The sequence incorporated steps typical of ballet, was recorded silently without music or verbal cues, and was presented to participants using the Pavlovita data collection software.

Procedure

Participants sat in front of a computer and watched the video of the dance sequence. Participants viewed the sequence five consecutive times. Before the first viewing of the choreography, participants read the following instructions and were tasked with segmenting the dance:

"You will now see a video clip of a dancer performing part of a choreography. While watching, please keep your finger on the space bar and press it each time a part of the dance phrase ends and a new one begins. Apply your own criteria: you do not need to mark the same moments in each repetition."

During the next three viewings, participants were tasked with only watching the choreography. Then on the fifth viewing,

they were again tasked with segmenting the dance. After completing the segmentation task, participants answered a strategy and demographic questionnaire to assess the explicit or deliberate criteria used during segmentation, following methods from Bläsing (2015). Dance experience was assessed through a questionnaire asking about years of formal dance training, genres studied, and frequency of practice.

Data Analysis

Three analyses were conducted. First, the mean number of segments identified by each participant was calculated. Each bar press was taken to represent a boundary between segments. The maximum number of segments per participant was 49, which could be obtained if they made a bar press after each individual step.

Then, two other measures were developed to try to capture the amount of agreement that existed across individuals in their segments. One measure, adapted from Kurby and Zacks (2008), evaluated the similarity in boundary choices to other participants. This was done by computing a correlation for each individual, between making a bar press (or not) on each step, and the likelihood that others made a bar press on that step (i.e., the group average). Since the number of bar presses varied across individuals, agreement was standardized using the approach from Kurby and Zacks to adjust for minimum and maximum possible values using the formula:

$$\text{Agreement} = \frac{r - r_{\min}}{r_{\max} - r_{\min}}$$

In this formula, r represents the correlation with the group average, r_{\min} is the minimum possible agreement, and r_{\max} is the maximum possible agreement. Higher correlations represent more similarity in the perceived structure of the dance.

Another approach looked at differences in segment assignments for each step, similar to card sort procedures used to reveal the organization of domain knowledge in studies of categorization, such as research on dinosaurs by Chi et al. (1989) and tree experts by Medin et al. (1997). Participant assignments for each step where segments served as categories were compared to the assignment suggested by the majority of the experts. For example, if experts placed the 15th dance step within the third segment, a participant who placed it in the fourth segment would receive an error score of 1 for that step, and a participant who placed it in the sixth segment would receive an error score of 3. Error scores were averaged across all steps for each participant. Higher error represents less similarity in the perceived structure of the dance.

These two measures capture different aspects of segmentation agreement. Boundary agreement evaluates whether participants placed segmentation boundaries at the same point as the group. This treats each step as a binary choice (boundary vs. no boundary) and is standardized by comparing an individual's segmentation pattern to the group average and adjusting for minimum and maximum possible agreement, ensuring that no step is overvalued. In contrast, the error score measure assesses step-by-step deviations from

expert-defined segmentation by quantifying how far a participant's assigned segment for each step deviates from the expert consensus. Unlike boundary agreement, this measure accumulates error, meaning that an early misalignment can result in a high error score even if later segmentations align with the expert-defined structure. Employing both cumulative and noncumulative measures of similarity provides complementary approaches for assessing agreement. Ultimately, boundary agreement captures general similarity in segmentation patterns, while error scores reflect the magnitude of deviation from the expert average.

Results

Due to the unequal group sizes of experts ($n = 5$) and novices ($n = 40$), Welch's t-tests were conducted to compare group differences. Paired sample t-tests were conducted to compare across time points.

Number of Segments

As shown in Figure 1, experts identified significantly fewer segments than novices for the ballet sequence at both the first viewing, $t(11.42) = 2.70, p = .020, d = 0.86$, and the fifth viewing, $t(14.53) = 3.33, p = .005, d = 0.99$. This suggests that experts formed fewer, larger chunks.

There was a trend for the number of segments to decrease from the first to the fifth viewing, $t(44) = 1.83, p = .074$. The decrease was marginal for novices, $t(39) = 1.71, p = .095$, while the number of segments for experts remained similar, $t(4) = 0.64, p = .558$.

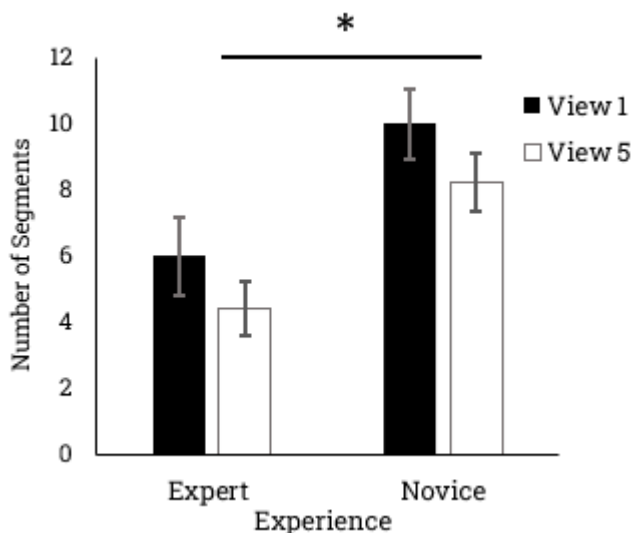


Figure 1: Effects of Expertise and Viewing on Segment Number. Error bars represent the standard error of the mean.

Boundary Agreement

As shown in Figure 2, boundary agreement scores differed significantly between experts and novices. Experts demonstrated higher agreement at both the first viewing,

$t(5.41) = -6.93, p < .001, d = -3.11$, and the fifth viewing, $t(7.17) = -6.18, p < .001, d = -2.34$. This suggests that experts are perceiving the same chunks as each other. No differences were found between the first and fifth viewing for either experts. $t(4) = 1.71, p = .164$, or novices, $t(39) = 1.71, p = .095$.

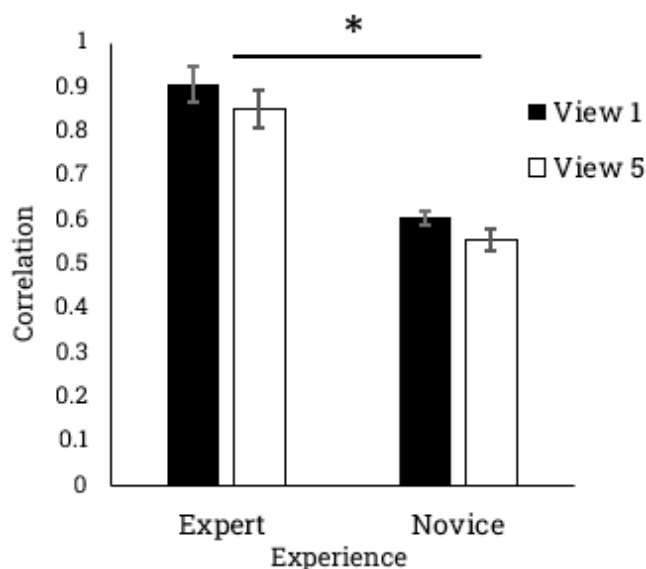


Figure 2: Differences in Boundary Agreement. Error bars represent the standard error of the mean.

Segment Assignment

As shown in Figure 3, experts were more likely to include dance steps in the same segments as other experts. Experts had lower error scores compared to novices at the first viewing, $t(11.32) = 3.33, p = .006, d = 1.06$, and the fifth viewing, $t(36.15) = 3.26, p = .002, d = 0.81$ viewing. This also suggests that experts are perceiving the steps as part of the same chunks as each other.

There was a significant decrease in the error scores from the first to the fifth viewing, $t(44) = 2.23, p = .031$. The decrease was significant for novices, $t(39) = 2.71, p = .036$, while the error scores for experts remained similar, $t(4) = 0.57, p = .600$.

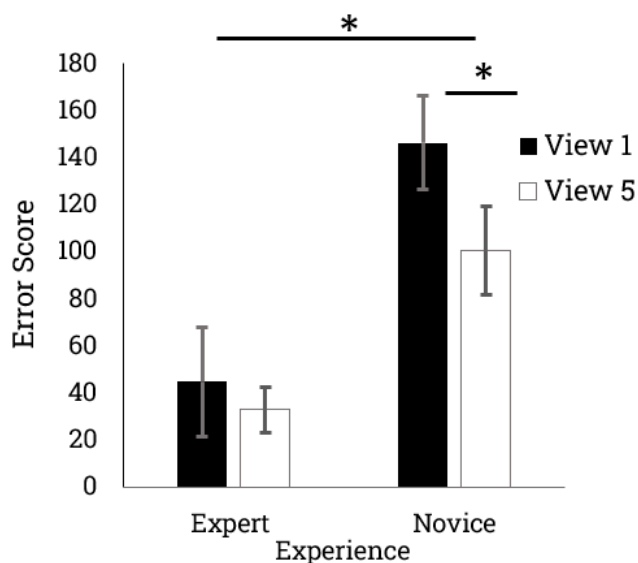


Figure 3: Differences in Segment Assignment. Error bars represent the standard error of the mean.

Correlations between Boundary Agreement and Segment Assignment Error Scores

Although these two measures were both intended to capture similarities in event models across individuals, they were not correlated (Spearman's $\rho = -.16, p = .12$), suggesting that they are tapping different aspects of segmentation.

Discussion

The expertise literature consistently demonstrates that prior knowledge profoundly influences memory for domain-related information. In chunk-based theories of expert memory, domain-specific knowledge allows experts to group related information into larger, meaningful units, or "chunks" (Chase & Simon, 1973; Gobet & Simon, 1996b). Similarly, EST posits that prior knowledge informs event models which are dynamic mental representations that can be used to predict transitions and identify meaningful boundaries during ongoing activity (Zacks & Swallow, 2007). This study builds on previous studies of expert memory for dance by applying EST to examine how expertise shapes the recognition of units in ballet choreography.

Although the expert sample so far is quite small, these initial results revealed that expert ballet dancers segmented the choreography into significantly fewer and larger chunks than novices. This finding aligns with previous research in domains such as chess, where experts group related elements into cohesive patterns to manage complex information (Chase & Simon, 1973; Gobet & Simon, 1996b), and also specifically in dance, where experts segment movements into larger units (Bläsing, 2015; Poon & Rodgers, 2000). These findings demonstrate that experts chunk dance choreography more efficiently than novices, which is likely due to their ability to perceive choreography as interconnected,

functional units rather than isolated movements (Bläsing et al., 2009).

In addition to forming larger chunks, experts with similar training exhibited greater consistency with each other in how they segmented the ballet sequence, as indicated by higher boundary agreement between steps and more similarity in segment assignments for each step compared to novices. These results suggest that experts are representing the dance in meaningful chunks, using long-term knowledge that has been shaped by their extensive training and experience. Their long-term knowledge is not just extensive, but is also well organized and incorporates the structure of the domain. This finding aligns with template theory, which posits that experts encode information using structured patterns (templates) with flexible slots for variable details (Gobet & Simon, 1996b). Experts' consistency in segmentation highlights their ability to recognize and utilize the structure of the dance to facilitate efficient encoding and retrieval of choreographic information.

The consistency of expert chunking was also observed across repeated viewings with no significant changes in both the number and agreement of chunks. This suggests that the experts were already able to engage in chunking after the first exposure. If the ability for experts to learn dances faster than novices that was seen in Adams et al. (2023) was due to experts' ability to update their chunking to better fit the choreography, we would have expected to see some variation over the course of the viewings. However, our results showed no significant differences in expert segmentation patterns across viewings, suggesting that experts did not drastically alter their event models with repeated exposure. Instead, expert chunks remained stable, reinforcing the idea that experts entered the task with a well-developed framework for organizing movement. Since there was no significant change in either agreement measure, our findings suggest that expertise is characterized more by an initial ability to recognize and apply domain-specific structures rather than a gradual process of restructuring over repeated viewings. It will be interesting to investigate what mechanisms or strategies might be responsible for sharp increases in expert memory from additional exposures. The next step in this line of research is to incorporate measures of chunking and measures of memory in the same study to more fully understand how dance experts are able to circumvent the limits of short-term memory, and what other strategies may be in play when they are learning very long dance sequences.

The current study employed two distinct measures to assess the similarities and differences in the segments perceived by experts and novices. The first measure, boundary agreement, is commonly used in EST to identify segmentation patterns in narratives and films. The second measure was based on card-sorting and categorization tasks. While both measures aimed to capture segmentation agreement, they did not end up correlating with each other. Future studies will incorporate both measures to determine which metric more accurately predicts advantages in memory

performance. Studies using implicit segmentation measures may also provide valuable insights.

Another avenue for future research is to explore differences in the ways dances are segmented across genres. Advantages in memory for dance sequences with expertise have not been consistently found across all genres, and there is no clear consensus on why this occurs (Deakin & Allard, 1991; Jean et al., 2001; Starkes et al, 1990). However, it is suspected that the way information is structured within a dance plays a significant role. Genres such as ballet, with its rigid structure and well-defined vocabulary, may lend themselves more easily to the formation of stable schemas. In contrast, modern dance, which allows for greater improvisation and fluidity, may not provide dancers with the same consistent patterns in long-term memory. A future study should explore how segmentation differs between structured and less-structured dance disciplines, examining whether the availability of domain-specific schemas influences how experts perceive and chunk movement sequences. Additionally, research could investigate how trained dancers from structured genres, such as ballet, segment unfamiliar, unstructured choreography, and vice versa. Furthermore, collecting larger samples of experts and comparing experts from different genres could provide insight into whether their segmentation patterns align with the structure of the choreography or with their pre-existing training, shedding light on the flexibility and limits of domain-specific schemas in expert memory.

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