The influence of expertise on segmentation and memory for basketball and Overwatch videos

by

Kimberly Marie Newberry

B.A., The College of New Jersey, 2014

A THESIS

submitted in partial fulfillment of the requirements for the degree

MASTER OF SCIENCE

Department of Psychological Sciences
College of Arts and Sciences

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2019

Approved by:

Major Professor
Heather Bailey

Copyright

Abstract

Much research has shown that experts possess superior memory in their field of expertise. This memory benefit has been proposed to be the result of various encoding mechanisms, such as chunking and differentiation. Another potential encoding mechanism that is associated with memory is event segmentation, which is the process by which individuals parse continuous information into meaningful, discrete units. Event Segmentation Theory proposes that segmentation is influenced by perceptual (e.g., motion) and conceptual (e.g. semantic knowledge) cues. Previous research has found evidence supporting the influence of knowledge on segmentation, specifically through the manipulation of goals and familiarity for everyday activities. To date, few studies have investigated the influence of expertise on segmentation, and questions about expertise, segmentation ability, and their impact on memory still remain. The goal of the current study was to investigate the influence of expertise on segmentation and memory ability for two different domains: basketball and Overwatch. Participants with high and low knowledge for basketball viewed and segmented basketball and Overwatch videos at coarse and fine grains, then completed memory tests. Differences in segmentation ability and memory were present between experts and novices, specifically for the basketball videos; however, segmentation only predicted memory for activities for which knowledge was lacking, for experts. Overall, this research suggests that experts' superior memory is not due to their segmentation ability and contributes to a growing body of literature showing evidence supporting conceptual effects on segmentation.

Table of Contents

List of Figures

List of Tables

Acknowledgements

A sincere thank you to everyone who has been involved with this project: Dr. Heather Bailey, Dr. Lester Loschky, and Dr. Joseph Magliano, for their tremendous guidance and constructive feedback throughout the entirety of this project; Daniel Feller, for help with stimuli development; Maverick Smith, for his help with statistical analyses; Destiny Bell and Dr. Barbara Pitts for their general feedback and support; Jennica Rogers and our team of undergraduate research collaborators, including Jaydan Bruna, Allison Griffin, Marissa Muto, Sydnee Pachek, Nicholas Parker, and Rebecca Ryan, for their help with data collection, data scoring, data entry, and general feedback.

Chapter 1 - Introduction

Decades of work on expertise have shown that experts possess superior memory for information in their field of expertise. This memory benefit has been explained by various encoding mechanisms, including chunking (combining meaningful information into larger units; Chase & Simon, 1973), differentiation (distinguishing between features) and unitization (holistic processing; Herzmann & Curran, 2011). Recently, another encoding mechanism has been suggested to influence memory for event information; event segmentation (Bailey et al., 2013; Flores, Bailey, Eisenberg, & Zacks, 2017; Newberry & Bailey, under review; Sargent et al., 2013; Zacks et al., 2006). Event segmentation is an encoding mechanism in which individuals parse continuous event information into meaningful, discrete units. How individuals segment an event influences how they perceive, comprehend, and remember events. This process may be influenced by both perceptual (e.g, motion) and conceptual (e.g., knowledge) factors, which suggests that prior knowledge or experience, such as expertise, may affect how an individual perceives and segments an event, which in turn may influence memory. To date, few studies have investigated the influence of expertise on segmentation (Blasing, 2015; Levine, Hirsh-Pasek, Pace, & Michnick Golinkoff, 2017; Zacks & Tversky, 2003) and questions remain about the extent to which expertise influences segmentation and memory. For example, to what extent do experts and novices agree as to how activities are segmented within and outside of one's expert domain? Does the way in which experts organize events at encoding differ from that of novices? What are the possible effects on memory? Additionally, the activities that have been investigated thus far (dance and figure skating) are what the motor-skill literature call *closed skills*, or skills "displayed by performance in a consistent, typically stationary, environment," (Ericsson & Smith, 1991, p. 126). It is unclear whether segmentation differences only arise in closed skill activities or whether the effects may extend to *open skills,* or performance in a moving, dynamic environment, such as team sports and video games.

To resolve these issues, the current study investigated the influence of expert knowledge on the segmentation and memory of basketball and Overwatch games. To lay the foundation, two theories of event cognition, Event Segmentation Theory and the Event Horizon Model, will be outlined, followed by the relationship between segmentation and knowledge. Afterwards, the literature on expertise will be described and integrated with event segmentation, and finally, general predictions about the current study will be outlined.

Event Segmentation Theory

One theory of event cognition that proposes an explicit role of knowledge in the perception and comprehension of events is Event Segmentation Theory (EST; Kurby & Zacks, 2008; Zacks, Speer, Swallow, Braver, & Reynolds, 2007). According to EST, individuals construct mental representations of incoming activity in the form of a mental model (e.g., event model for visual events; situation model for text; Radvansky & Zacks, 2014, 2017). Individuals use perceptual and conceptual information to generate this mental representation in the event model. Perceptual cues are information from the environmental about the event itself, such as motion and body position (e.g., Zacks, 2004), while conceptual cues refer to long-term memory features, such as familiarity and goals (Radvansky & Zacks, 2014, 2017; Zacks, 2004). The representation of the current event is held in working memory and is updated to reflect changes that occur in the real-life event. That is, when one event ends and another begins, working memory is “reset” so that a new representation, or event model, can be constructed to reflect the new event that is unfolding. It is at these points in time when individuals typically perceive event boundaries (i.e., the breaks between events).

Research has suggested that events are hierarchically structured, such that larger, coarse-grain events are made up of smaller, fine-grain events (Tversky, Zacks, & Martin, 2008; Zacks & Swallow, 2007; Zacks, Tversky, & Iyer, 2001). For instance, coarse-grain events, such as making breakfast, consists of smaller sub-events, such as taking the frying pan out of the cupboard, taking the eggs out of the refrigerator, and turning on the stove. Previous work has found individual differences in the extent to which people perceive alignment between the fine-grain and coarse-grain events (e.g., Hard, Lozano, & Tversky, 2006; Kurby & Zacks, 2011; Sargent et al., 2013; Zacks, Braver, et al., 2001), and there is evidence to suggest that this hierarchical encoding may be important for memory (Kurby & Zacks, 2011).

Additionally, individuals tend to agree on the locations of perceived event boundaries, for both fine and coarse event boundaries, and show good inter-subject reliability (Bower, Black, & Turner, 1979; Hard, Tversky, & Lang, 2006; Newtson, 1973; Speer, Swallow, & Zacks, 2003; Zacks et al., 2001). It is quite impressive that of all the possible locations at which people can segment, they tend to agree on similar locations. For example, they can agree with themselves even up to one year later (e.g., test-retest; Speer, Swallow, & Zacks, 2003). Importantly, the extent to which people demonstrate normative segmentation (i.e., they agree on locations of event boundaries) predicts how well they remember the activity at a later time (Bailey et al., 2013; Flores et al., 2017; Newberry & Bailey, under review; Sargent et al., 2013; Zacks et al., 2006).

Event Horizon Model

One model that provides a mechanism for why segmentation ability influences episodic long-term memory is the Event Horizon Model (EHM; Radvansky, 2012). The EHM is comprised of five principles that describe how event representations are developed, changed, and remembered over time (Radvansky & Zacks, 2017). The first principle describes an event segmentation mechanism (similar to the segmentation mechanism proposed in EST) and the second principle states that the current event model is solely contained in working memory. The third principle describes how causal connectivity is the main organizational tool, creating relations between events. The fourth principle describes how memory benefits from event boundaries when the goal is to remember as much as possible about an event, and finally, the fifth principle describes how memory can be impaired when similar information competes across multiple event models.

Of the five principles of EHM, the first and fourth are the most relevant to the current study. Specifically, one of the main goals of the current study was to evaluate the effects of knowledge on segmentation and their potential effects on memory. According to the fourth principle of EHM, event boundaries are important for memory because they reduce retroactive interference by separating information into different event models, which leads to better overall memory for the activity (Radvansky & Zacks, 2017). In the current study, individuals who segment more effectively should experience less retroactive interference and have better memory for the activities. This effect should be especially strong for those who have expertise in a domain. That is, if knowledge enhances segmentation ability, memory may show an even stronger benefit.

Perceptual and Conceptual Influences on Segmentation

As mentioned above, two types of factors have been suggested to influence segmentation: perceptual and conceptual (e.g., EST; Zacks et al., 2007). Much of the research on event segmentation has focused on the influence of perceptual cues. Prior research has shown that perceived event boundaries tend to align with moments in which a greater number of feature changes, such as changes in body position (Newtson, Engquist, & Bois, 1977) and spatial location (Magliano, Miller, & Zwaan, 2001).

For instance, Zacks et al. (2001) investigated the hierarchical structure of events by having participants watch, segment, and verbally describe videos depicting everyday activities (e.g., washing dishes, making the bed). Participants segmented at both coarse and fine units and demonstrated hierarchical alignment, such that the coarse units tended to line up with the final segments of finer units, more often than chance. In addition to this, the results suggested that the participants' event segmentation was driven by motion associated with action, thus providing some support for perceptual cues guiding event structure perception.

Relatedly, Hard et al., (2006) investigated whether the hierarchical perception of events depends on prior knowledge of intentions by having participants watch abstract and schematic films. They found that regardless of familiarity, movement features predicted segmentation and that perceived event boundaries corresponded to bursts of perceptual change, particularly in line with coarser units. Furthermore, neuroimaging studies have found increased neural activity in motion processing areas of the brain, such as the extrastriate motion complex (MT+), when event boundaries are perceived during an event (Speer et al., 2003; Zacks, Braver et al., 2001). Such results suggest that motion is a strong predictor for the perception of event boundaries.

In contrast to perceptual features, conceptual factors are semantic knowledge structures from long-term memory that aid in interpreting perceived events based on previous experiences (Zacks, 2004). There are a variety of conceptual features that may influence moment-to-moment event perception, such as context and perspective (Newberry & Bailey, under review), schema and scripts (Bartlett, 1932; Newberry, Smith, & Bailey, in prep; Schank & Abelson, 1977), intentions (Hard et al., 2006) and goals (Baldwin, Baird, Saylor & Clark; 2001; Wilder, 1978a;

Wilder, 1978b; Zacks 2004). Much of the research that has investigated the influence of conceptual factors has focused on the roles of intentions and goals. For example, Wilder (1978a, 1978b) showed that the frequency of segmenting a movie, in which an actor performed goal-directed activities, changes based on the predictability of an event. Specifically, participants segmented more often when the goals of the actor were unclear and less often when the activity was goal-directed and predictable. Relatedly, evidence from infant studies supports the use of goals in parsing event-related information. Baldwin et al. (2001) assessed looking time in infants aged 10-11 months as they viewed short-sequence movies depicting goal-directed activities. When important information related to goal completion was obscured, looking time increased, suggesting that the infants used goal-related activity to parse incoming information.

Additional findings support the influence of conceptual factors on segmentation. Zacks (2004) conducted a series of experiments in which movement features and goal-related inferences were manipulated while participants viewed simple animations. Movement certainly predicted segmentation; however, the strength of its prediction depended on the saliency of the goal-directed activity. When the movements in the animations were random, the relationship between movement and segmentation was stronger than when the animations depicted goal-directed activity. Similarly, Zacks, Speer, and Reynolds (2009) found that changes in situational features, such as character, location, and object interaction changes corresponded to points in time when individuals perceive event boundaries, in both text and film. These results suggest that when goal related knowledge is present, individuals rely less on perceptual cues while perceiving an event.

Knowledge and Segmentation

Though the aforementioned studies have provided some support for the influence of conceptual factors on segmentation within individuals, they have not directly manipulated semantic knowledge or investigated the relationship between semantic knowledge, segmentation agreement, and memory across individuals. However, recent studies have begun to explore this relationship (for a quick overview see Table 1 below).

Table 1. Brief Overview of Knowledge and Segmentation Studies

Influences of Knowledge on Different Measures of Segmentation

IV	Study	DV
Context		
	Loschky, Larson, Magliano, & Smith (2015)	
		Segmentation Agreement
	Newberry & Bailey (under review)	
		Segmentation Frequency Segmentation Agreement
Expertise		
	Blasing (2015)	
		Segmentation Frequency
	Levine et al., (2017)	
		Segmentation Frequency Sub-event Agreement Sub-event Alignment
	Zacks & Tversky (2003)	
		Hierarchical Alignment
Perspective		
	Newberry & Bailey (under review)	
		Segmentation Frequency Segmentation Agreement
Scripts		
	Newberry, Smith, & Bailey (in prep)	
		Segmentation Frequency Segmentation Agreement
	Smith, Newberry, & Bailey (in prep)	
		Dwell Time Segmentation Frequency Segmentation Agreement

Note: Independent variable (IV); Dependent variable (DV).

Newberry and Bailey (under review) investigated the influence of context (Experiment 1a) and perspective (Experiment 1b) on segmentation and recall, using methods borrowed from Bransford and Johnson (1972) and Anderson and Pichert (1978). In Experiment 1a, participants were presented with a series of ambiguous passages and were either presented with a title (context) or no title (no context) for each. In Experiment 1b, participants were presented with a longer story describing the events of two boys playing hooky from school. Participants were randomly assigned to read the story from the perspective of either a burglar or a homebuyer. Across both experiments, the participants were asked to read each passage, recall as much information as possible from each, and segment each passage. Individuals given context correctly recalled more idea units from the passages, replicating Bransford and Johnson (1972) and recalled more information that aligned with their perspective, replicating Anderson and Pichert (1978). Importantly, these conceptual manipulations influenced segmentation such that agreement was higher for individuals given context and for individuals within the same perspective group, albeit the effect sizes were modest to small. However, segmentation only predicted memory in Experiment 1b. These findings suggest that semantic knowledge can influence the amount of information remembered about an event and how that event is segmented, but the relationship between knowledge, segmentation, and memory remains unclear.

Moving from text to video, Loschky, Larson, Magliano, and Smith (2015) adopted a different manipulation of prior knowledge, using a jumped-in-the-middle context paradigm, to investigate conceptual effects on comprehension, segmentation, and eye-movements in film. Participants were asked to watch a film clip, but the points at which they started watching the film clip varied. Half of the participants saw extra frames in the beginning that provided important contextual information for comprehending the entire clip, whereas the other half of participants did not. Loschky et al. (2015) found that participants' segmentation of the film clip was different depending upon whether they saw the extra footage or not, suggesting that prior knowledge or context can influence how people segment and perceive the event structure of film.

A series of newer studies from Newberry, Smith, and Bailey (in prep) and Smith, Newberry, and Bailey (in prep) recently investigated the influence of age and knowledge on segmentation, dwell time, and memory for everyday activities (e.g., laundry, gardening, shopping). In these studies, knowledge was manipulated as the extent to which the different age groups produced normative scripts for the activity (Rosen et al., 2003) and was termed *familiarity*. For example, the older adults produced more normative scripts for activities such as gardening and balancing a checkbook, whereas the younger adults produced more normative scripts for activities such as grocery shopping and laundry. Though preliminary results suggest that familiarity did not influence event segmentation as measured by the unitization task, it did influence dwell time. Specifically, younger and older adults spent more time viewing information at boundaries, compared to non-boundaries, but this effect was much larger when they were viewing familiar activities. Further, memory was better for familiar activities in both age groups. Altogether, this study provides preliminary evidence in support of conceptual effects on covert measures of segmentation.

Expertise and Segmentation

Other work has adopted a different approach to evaluating knowledge effects on segmentation and hierarchical organization of information at encoding by focusing on expertise. Zacks and Tversky (2003) manipulated task instructions (structured or unstructured) and interface of instructions (text and pictures vs. text and video) to investigate the influence of structure and interface on task performance (reconstructing an object) and memory. Participants familiarized themselves using their assigned instructions, then attempted to reconstruct a saxophone (Experiment 1) or a mechanical bug (Experiment 2), and then recalled the steps of assembly. The results demonstrated that hierarchical organization at encoding is more likely to affect memory than object reconstruction and is more beneficial when used to convey order, as opposed to when order is not constrained. The results also suggested a trade-off between the usefulness of perceptual and conceptual influences in interfaces, such that perceptual factors facilitate assembly better when there are limited orders of assembly, and that conceptual factors facilitate assembly better when there are multiple correct orders of assembly. Ultimately, however, Zacks and Tversky (2003) concluded that conceptual factors are generally not sufficient in guiding performance, but that more research spanning different types of tasks is needed.

In the domain of dance, Blasing (2015) investigated the influence of domain expertise and movement-specific familiarity on the segmentation of a dance phrase. Dancers and non-dancers watched and segmented videos of a dancer completing a choreographed phrase. Blasing (2015) found that dancers segmented less often compared to non-dancers, suggesting that expertise reduces the number of perceived event boundaries for events within one's area of expertise. In this quasi-experiment, differences in segmentation behavior were observed between naturally occurring groups (experts and novices), but in another experiment, Blasing evaluated the causal role of knowledge on segmentation by manipulating familiarity with the activity. Intermediate dancers watched and segmented a dance phrase, then learned and practiced these motor movements, and finally segmented the dance phrase again. Results replicated the first study in that increased familiarity with the dance phrase and motor-experience with the movement caused dancers to segment less often.

Relatedly, in a series of studies, Levine et al., (2017) investigated the influence of prior knowledge on event boundary identification in Olympic figure-skating, using an expert-novice paradigm. Experts as well as novices who were familiarized with the skating sequence and unfamiliarized novices were asked to mark boundaries as a video of the skating routine progressed. Levine et al. (2017) found that experts identified more similar coarse-grain events compared to the novices, suggesting that experts have more normative event boundary perception. While they found that familiarized novices showed better alignment compared to true novices, they found that experts showed even better alignment of coarse-grain events, suggesting that the structure of events may be influenced by expertise, and not just familiarity.

Altogether, these studies have provided initial evidence supporting the influence of semantic knowledge on segmentation behavior; however, several gaps and limitations remain. For example, in the context and perspective study by Newberry and Bailey (under review), segmentation was restricted to the sentence level, rather than the idea unit level. One sentence could contain multiple idea units, which means that specific idea units could have been recalled, rather than entire sentences. This is relevant to segmentation because it is unclear whether, if given the opportunity, people would have identified event boundaries that would have coincided with specific idea units, for example, in sentences containing more than one idea unit. Thus, this discrepancy could have masked the influence of knowledge on segmentation count as well as influenced the relationship between segmentation and memory. Additionally, familiarity for the events described in the passages was not considered.

In the studies investigating age and knowledge, Newberry, Smith, and Bailey (in prep), and Smith, Newberry, and Bailey (in prep), used activities that are supposed to vary in familiarity by age. However, many of the younger adult activities (e.g., grocery shopping, laundry, getting ready for work) are activities that older adults still engage in, and, in some instances, may technically have more years of experience completing. Thus, it is uncertain whether their operational definition of familiarity is a strong enough manipulation of knowledge, given that it is difficult to control people's prior experiences with such every day activities.

As for Blasing (2015), this research evaluated segmentation frequency (i.e., how often people segment), not segmentation agreement, or memory for the activity. Though Levine et al., (2017) did investigate a coarse-grain segmentation agreement and found higher agreement among experts, hierarchical alignment of coarse and fine boundaries, as well as memory, were still not investigated; thus, the relationships between expertise, segmentation agreement, alignment among coarse and fine boundaries, and memory is still unknown. Additionally, one could argue that dance and figure skating are physical activities that share similar features (e.g., closed skills, Ericsson & Smith, 1991), thus it is also unclear whether results from these studies would replicate using different activities, especially open-skill activities such as sports and video games. Importantly, neither Blasing (2015) nor Levine et al., (2017) investigated experts' segmentation ability in a domain outside their expertise. That is, both studies used a quasi-experimental design in which participants could not be randomly assigned to the expert and novice groups; therefore, neither can rule out whether differences in segmentation ability can be explained by other potential differences in cognitive ability.

Given that effective segmentation has been found to predict better memory for events (Bailey et al., 2013; Flores et al., 2017; Zacks et al., 2006), it is possible that the superior memory of experts may be due to more efficient segmentation (evidenced by higher segmentation agreement or better hierarchical structure of coarse and fine boundaries; Radvansky & Zacks, 2017). If this were the case, one would expect individuals with more versus less knowledge for the same event to segment and remember the event differently. Likewise, one might expect this benefit to only be present within the expert's field of expertise and not due to some general superior segmentation ability.

Expertise

The term *expert* refers to those individuals who display outstanding behavior in or superior knowledge for a given domain. Much of the work on expert knowledge has shown that it facilitates memory for domain-relevant information (e.g., dance - Allard & Starkes, 1991; chess - Chase & Simon, 1973; baseball – Chiesi, Spilich, & Voss, 1979; bridge - Engle & Bukstel, 1978; maps – Gilhooly, Wood, Kinnear, & Green, 1988; music - Meinz & Salthouse, 1998). Expertise also facilitates problem-solving (e.g., baseball – McPherson, 1993; Voss, Greene, Post, & Penner, 1983) and comprehension for domain-relevant information in text (e.g., Spilich, Vesonder, Chiesi, & Voss, 1979; Recht & Leslie, 1988; Walker, 1987).

Of all the areas in which expertise has been studied, chess has been the most heavily investigated. Early studies using chess experts showed that experts' experience facilitated better performance on various memory measures, including free recall (e.g., Chase & Simon, 1973; De Groot, 1966) and recognition (Goldin, 1979). However, the memory benefit was only present when meaningful (realistic) plays were set up on the board. The results from these studies suggested that better memory performance was a product of increased familiarity with perceptual chess patterns and greater knowledge about the specific strategies and terms corresponding to those patterns rather than a domain-general superior memory ability.

Many different theories have been put forward to try to account for the superior memory benefit exhibited by experts (particularly chess experts, Herzmann & Curran, 2011), including chunking theory (pairing perceptual patterns with actions to create *productions* - Chase & Simon, 1973), template theory (more complex chunks - Gobet & Simon, 1996), and intuition theory (template theory combined with intuition – Gobet & Chassy, 2008).

Previous work has suggested that the memorial benefits of expertise are a result of more effective perceptual processing (Herzmann & Curran, 2011). For example, experts are more likely to identify domain-relevant objects at the subordinate level, whereas novices tend to categorize objects at the basic level (e.g., Bukach, Gauthier, & Tarr, 2006; Tanaka & Curran, 2001). Additionally, Goldstone (1998) proposes that two mechanisms are involved in perceptual learning: differentiation and unitization. Differentiation refers to the ability to separate initially-fused categories from one another and unitization refers to the ability to integrate individual parts into functional wholes. Both of these mechanisms may support the efficient processing of expertise, such that experts better judge when to engage in each process (Herzmann & Curran, 2011).

These enhanced perceptual processing abilities suggest that while encoding dynamic activity, experts might be better able to identify or agree on conceptual units of information and distinguish between fine details for events within their area of expertise. For example, when prompted to identify fine grain events of an activity in their field of expertise, experts may engage in differentiation, or be better able to distinguish between fine details of activities, compared to novices who might only be able to distinguish between a subset of the events. For example, a basketball expert may be better able to identify the components of a *pick and roll* while a novice might perceive that move as one unit or not at all. When prompted to identify coarse grain, perhaps conceptual, events, experts might engage in unitization, or be better able to combine smaller units of activity into cohesive, meaningful wholes. For example, a basketball expert might identify a rebound as part of an entire play whereas a novice might identify a rebound as its own separate event. If the boundaries that experts identify are meaningful and based on a shared knowledge base for the activity, one might expect experts to also agree more on the boundaries or units that are identified.

In addition to these types of superior perceptual processing abilities, experts also engage in strategic adaptations to task demands or processing constraints (Ericsson & Smith, 1991; Gobet & Simon, 1996). For example, in terms of superior memory, experts use specific chunking strategies to increase the number of items they can store in working memory (Ericsson et al., 2004, Thompson et al., 1993). Relatedly, Rawson and Van Overschelde (2008) found that experts use their knowledge to improve their organizational processing. They proposed that experts' superior memory is a result of specific encoding processes that allow experts to structure the incoming information in an efficient way. Taken together, the research on expertise suggests that experts' improved memory is a result of efficient encoding processes that integrate perceptual and conceptual information.

It is possible that experts may segment information in their domain differently than do novices. For example, in a visual search study evaluating differences in eye-movements in expert volleyball players compared to novices (Piras, Lobietti, & Squatrito, 2010), it was found that experts made fewer fixations with longer durations, specifically looking at the setter's hands, whereas novices spent more time fixating the ball trajectory. Overall, this study suggested that experts extract more task-relevant information than do novices. It is possible, then, that experts may agree more with other experts on the locations of perceived boundaries if they agree on the relevant task-information.

In a similar vein, experts might also exhibit better hierarchical alignment of coarse and fine events. The eye-movement differences between experts and novices in the volleyball study hint at the idea that experts pay more attention to more task-relevant, arguably meaningful or conceptual, information, while novices pay more attention to frequent perceptual changes (Piras et al., 2010). Such a result would align well with that of Zacks (2004) who found that perceptual changes more strongly guided segmentation when the activity was random (i.e., unpredictable).

Sargent et al. (2013) specifically investigated the influence of event knowledge on segmentation, including hierarchical alignment, and memory for everyday events. They found that segmentation and event knowledge uniquely predicted memory; however, hierarchical alignment was not affected by knowledge and did not predict memory. Though initially this suggests that hierarchical alignment differences may not be found between groups with different levels of knowledge, it is possible that the measure of event knowledge used in Sargent et al., (2013) was subject to too much variability. For example, most people are familiar with everyday tasks, such as making breakfast. Yet, how one person makes breakfast does not necessarily map on to how you or anyone else makes breakfast, which could have led to idiosyncrasies in the identification of coarse and fine boundaries. Thus, a stronger manipulation of knowledge, such as expert knowledge for specific activities, might be more sensitive to potential differences in hierarchical alignment and its influences on memory.

Importantly, segmentation ability is a unique predictor of memory above and beyond other cognitive abilities (Sargent et al., 2013). It is possible then that segmentation may partially explain experts' superior understanding and memory for domain-relevant information. However, as previously stated, neither Blasing (2015) or Levine et al., (2017) investigated the effects of expertise and segmentation on memory. Though Zacks and Tversky (2003) did include memory, they suggested investigating these relationships in other domains, as familiarity with general object assembly may have influenced their results. Additionally, neither Blasing (2015) nor

Levine et al., (2017) included an activity outside the expertise domain of their experts, so it is unclear whether experts' seemingly more efficient segmentation ability is domain specific or a general processing ability that extends to other domains as well. The current study expanded upon Blasing (2015) and Levine et al., (2017) by directly investigating segmentation behavior and its relationship to memory performance in experts and novices, across two domains, both of which are different from dance and figure skating; specifically, basketball (sport) and Overwatch (video game). In Experiment 1, an Overwatch knowledge survey was developed for use in Experiment 2, in which experts and novices were identified using the knowledge surveys and completed segmentation and memory tasks for basketball and Overwatch videos.

Basketball and Overwatch were chosen as the activities of interest in this study for a few reasons. First, the inclusion of two activities makes the current study unique in that experts were tested on activities both within and outside their field of expertise. Second, basketball and Overwatch are open skills (dynamic) whereas dance and figure skating are closed skills (constrained; Ericsson & Smith, 1991). Evaluating segmentation ability for open skills would allow generalizations to be made across activity types. Relatedly, basketball and Overwatch are very different from one another, which allows for segmentation to be tested across very different domains. Basketball is a limited-contact, team-based sport that involves players working together to achieve a common goal (i.e., shooting the ball through the hoop to earn points). Overwatch, though also team-based, is a multiplayer first-person shooter video game that is played on the computer. Game objectives, such as defending a specific location or escorting an object to a location, differ depending on the game map chosen. Third, availability of participants was also a relevant factor for activity choice. Basketball is commonly played and watched in the Mid-Western United States. Similarly, Overwatch is a very popular video game (Ranker, 2018), and is routinely played in eSports organizations on college campuses (including Kansas State University) for sport and scholarship (Bauer-Wolf, 2017).

Chapter 2 - Research Questions and Hypotheses

Unless otherwise stated, the predictions presented below apply to both the between- and within-subjects relationships.

Does Expert Knowledge Influence Event Segmentation?

The Conceptual Hypothesis

Based on the results of Blasing (2015) and Levine et al., (2017), we hypothesized that experts would segment less often (*segmentation count*), regardless of segmentation grain, and agree more on boundary locations (*segmentation agreement*), for activities within their field of expertise. We also hypothesized that experts would show greater hierarchical alignment of coarse and fine boundaries for activities within their area of expertise (*hierarchical alignment*). Evidence for these hypotheses would suggest that experts engage in more efficient chunking strategies and use their long-term knowledge stores to guide similar and more efficient encoding of the incoming information.

The differentiation hypothesis. It is possible that experts may segment more often than novices during activities in their field of expertise. If this were the case, this would suggest that experts engage in more differentiation while encoding within-domain information than do novices. This hypothesis still supports a conceptual influence of knowledge on segmentation, but in the opposite direction of what has been found.

The Perceptual Hypothesis

Evidence against the conceptual hypotheses would suggest that segmentation processes are influenced primarily by perceptual factors, such as movement, because perceptual information would be equally available to both experts and novices. In this case, segmentation behavior (frequency, agreement, and hierarchical alignment) exhibited by experts and novices would be similar, regardless of activity.

Does Expert Knowledge Influence Memory?

The Expertise Hypothesis

Based on the significant body of expertise literature (for review see Ericsson & Smith, 1991), we hypothesized that experts would show better recognition and order memory performance for activities within their field of expertise. Evidence for this hypothesis would suggest that expert knowledge positively influences memory for expert domain information.

The Surprising Hypothesis

An alternative hypothesis would be that knowledge is not found to influence recognition and order memory for activities within the field of expertise. However, this would be surprising given the decades of prior work (for review, e.g., Ericsson & Smith, 1991) and might instead suggest a methodological issue with the tasks.

Does Segmentation Ability Predict Memory and Is This Relationship Moderated by Expert Knowledge?

The Segmentation Benefit Hypothesis

Previous work suggests that normative segmentation is associated with better memory for events (Bailey et al., 2013; Flores et al., 2017; Sargent et al., 2013; Zacks et al., 2006). Segmentation uniquely predicts memory above and beyond many other cognitive abilities (Sargent et al., 2013) and this relationship lasts for up to one month (Flores et al., 2017), indicating that it is an important process for event comprehension and memory. Based on this work, we hypothesized that segmentation ability (both agreement and hierarchical alignment) would predict memory performance, regardless of activity or expert knowledge. If experts and novices show similar relationships between segmentation and memory, this would suggest that conceptual influences on segmentation only minimally improve memory above and beyond segmentation based on perceptual cues.

The rich-get-richer hypothesis. Further, we predicted that this relationship would be stronger for those with expert knowledge in their area of expertise. This would be a “rich-get-richer” hypothesis (Hambrick & Engle, 2002), because those who have expertise should segment more effectively and have even better memory.

The poor-get-richer hypothesis. It is possible that novices may show a stronger relationship between segmentation and memory compared to experts. This would suggest that segmentation ability may be particularly important for memory when one lacks knowledge, or has impoverished schemata to rely on, for the activity. If novices show a relationship between segmentation agreement and memory and experts do not, this would suggest that expertise might influence memory through mechanisms other than segmentation.

The Null Hypothesis

It is possible that segmentation may not benefit memory, regardless of knowledge. Such an effect would be surprising given prior research.

Chapter 3 - Experiment 1: Overwatch Knowledge Survey Development

The purpose of Experiment 1 was to develop a survey that could differentiate between individuals with high and low knowledge for the video game, Overwatch. A battery of questions was presented online to participants with the intent of narrowing down the top questions for use in Experiment 2. To date, no research has developed an Overwatch knowledge survey for research purposes, thus the parameters of the survey in the current study were based on previous research that used knowledge surveys for football (Rawson & van Overschelde, 2008) and basketball (Feller, Schwan, Wiemer, & Magliano, in prep, adapted from French & Thomas, 1987).

Method

Participants

A total of 142 individuals (Final N = 102; 12 Experts, 71 Novices, 19 Intermediates) were recruited online from Amazon Mechanical Turk (M-Turk). M-Turk is an online server through which individuals can earn money for completing online experiments, usually surveys and questionnaires. Incomplete surveys were excluded from data analysis (n = 40). On average, participants took approximately 5 minutes and 30 seconds to complete the survey and were paid $.50 for their time.

Materials

A questionnaire consisting of 38 multiple-choice questions was created using Qualtrics software to assess general knowledge of Overwatch (for the final version of the Overwatch survey, see Appendix A). The goal was to identify the top 23 questions for use in Experiment 2, which was based on predicted time and survey length restrictions imposed by the pre-screen requirements through the SONA experiment server implemented by Kansas State University. Each question had 1 correct answer out of 5 total answer options, with the fifth option (e) always stating "I don't know," (Rawson & van Overschelde, 2008). The content of these questions concerned various aspects of Overwatch, including development (e.g., Which company developed Overwatch?), game rules (e.g., Which of the following is not a method of earning in-round fire points?), characters (e.g., Which character role forms choke points for enemies?), plays or strategies (e.g., A "critical hit" is synonymous with which of the following?), and storyline (e.g., What are the names of the two characters who were in charge of Overwatch?). All the information used to generate these questions came from personal research on Overwatch wiki sites (https://overwatch.gamepedia.com/Overwatch_Wiki) and the company (Blizzard Entertainment ©) website (https://www.blizzard.com/en-us/).

Seven self-report questions were included after the general knowledge portion of the survey. These items assessed self-reported familiarity and expertise for Overwatch and 6 of the 7 questions had 5 answer options (Table 2). The remaining question asked participants to manually enter in their Skill Rating (SR; ranges 1-5000). SR is a measure of skill used to determine Overwatch players' experience in competitive play. Participants were instructed to enter "0" if they did not play Overwatch (i.e., were novices).

Design and Procedure

A within-subjects design was used, such that all participants saw all questions, in the same order. The experiment was posted to M-Turk. Once participants clicked on the link to participate, they were directed to the Overwatch survey, which was hosted online through Qualtrics. Participants indicated their consent to participate by clicking a button on the informed consent form screen. After giving consent, instructions appeared on screen, informing participants that they would be answering questions about a specific activity and that they should rely on their own knowledge, not outside resources, to answer each question. Next,

Table 2. Self-Report Questions and Answers for Overwatch Survey

Overwatch Self-Report Survey Questions and Answer Options

Question	Option A	Option B	Option C	Option D	Option E
I have a high level of Overwatch knowledge.	Strongly disagree.	Somewhat disagree.	Neither agree nor disagree.	Somewhat agree.	Strongly agree.
Please choose the option that best describes your involvement with Overwatch.	I currently play Overwatch.	I used to play often, but not anymore.	I used to play a little, but not anymore.	I have seen people play Overwatch, but I have never played.	I have never seen people play Overwatch and I have never played.
How often do you play Overwatch?	Daily	Weekly	Monthly	Yearly	Never
If you do play, please select the approximate number of hours per week that you spend playing Overwatch. If you do not play, please choose 0.	0	1-5	6-10	11-15	16 or more
I consider myself an Overwatch expert.	Strongly disagree.	Somewhat disagree.	Neither agree nor disagree.	Somewhat agree.	Strongly agree.
Overwatch is hard for me to understand.	Strongly disagree.	Somewhat disagree.	Neither agree nor disagree.	Somewhat agree.	Strongly agree.

the content questions appeared. Once all the content questions were answered, participants responded to the self-report items. Afterwards, a debriefing form appeared on screen, and participants received an M-Turk code, which they then used to receive their compensation through M-Turk.

Results

Data Preparation

As mentioned above, only completed surveys were included in the data analysis. Forty-two participants did not finish the survey; therefore, any answers they may have indicated were not included in data analysis. Thresholds for “expert” and “novice” categorization were based on percentage cutoffs used by Rawson & van Overschelde (2008). In their study, novices scored 10 or less correct out of 28 items (.36), whereas experts scored 20 or more correct (.71). In the current study, participants categorized as novices scored 13 or less out of 38 items (.34) and participants categorized as experts scored 27 out of 38 (.71). Table 3 presents SR and Knowledge scores for the survey. Experts had significantly higher SR scores compared to novices and intermediates (p < .001). Experts also had significantly higher knowledge scores compared to novices and intermediates (p < .001). The correlation between SR and Knowledge was r = .71.

Table 3. Skill Rating and Knowledge Scores by Expertise Group

Skill Rating and Knowledge Scores by Expertise Group

	Novice	Intermediate	Expert
Skill Rating (SR)	9.69 (7.08)	258.47 (228.38)	2134.67 (340.13)
Knowledge Score	7.59 (.45)	17.16 (.74)	31.83 (1.49)

Note: Standard error in parentheses. Skill rating ranges from 0 – 5000. Knowledge scores range from 0 – 38.

Self-Report Questions

All participants answered self-report questions asking about their familiarity with and expertise for Overwatch. Experts significantly differed on self-reports of high knowledge in Overwatch (M = 3.83, SE = .37) from novices (M = 2.65, SE = .15), p = .01, and intermediates (M = 2.37, SE = .30), p = .01, such that they reported having more knowledge for the game. Novices disagreed more often with such statements. Experts also significantly differed on self-reported involvement (i.e., regularity (hours, days, etc.) of Overwatch game play; M = 1.67, SE = .37) from novices (M = 3.07, SE = .15), p = .002, and intermediates (M = 3.11, SE = .30), p = .01, such that they currently play or used to play often, either daily or weekly, while Novices reported either playing the game infrequently or never playing but watching others play the game. Overall, experts reported having higher knowledge and expertise in Overwatch compared to novices and intermediates. Experts also reported spending more time playing the game.

General Knowledge Questions

A series of independent samples t-tests using expertise (expert or novice) to predict the outcome of each question were used to determined which questions best discriminated between experts and novices. We corrected for familywise error by adjusting the alpha level from .05 to .0013 (.05/38; 38 questions). The top 23 questions were the questions that best discriminated between experts and novices at alpha .0013 (see Appendix A). Cronbach's alpha for the original 38 items was .96. Cronbach's alpha for the 23 items was .95, suggesting high internal consistency.

Discussion

The goal of this experiment was to determine which questions to include on an Overwatch knowledge survey that would discriminate between Overwatch experts and novices in Experiment 2. We created a battery of 38 questions using online resources specific to Overwatch game play, including rules, strategies, character information, and storyline. Overwatch experts and novices answered the questions and reported their familiarity with the game. Overall, experts reported higher familiarity and involvement with Overwatch. Experts also scored the highest on the questionnaire. Of those 38 questions, the top 23 were chosen for use in Experiment 2. These final questions were the items that best discriminated between Overwatch experts and novices.

Chapter 4 - Experiment 2: Expertise, Segmentation, and Memory

The purpose of Experiment 2 was to investigate the relationship between expert knowledge, segmentation ability, and memory for events within and outside of one's area of expertise. Previous work has observed effects of expertise on the segmentation of dance phrases (Blasing, 2015) and a figure skating routine (Levine et al., 2017); however, these studies have only evaluated experts' segmentation behavior for events within their field of expertise. Additionally, the hierarchical alignment of different segmentation grains and its effects on memory have yet to be evaluated in this context. In Experiment 2, basketball and Overwatch experts and control novices viewed and segmented videos of basketball and Overwatch. Unfortunately, due to high attrition and recruitment issues, only a very small sample of Overwatch experts were identified and participated in the study (see *Method*). This group's data were excluded from the main analyses and only included in exploratory analyses where expert knowledge was treated as a continuous variable. Thus, the current experiment ultimately focused on a within-subjects comparison of basketball experts' segmentation and memory for basketball (area of expertise) and for Overwatch (area outside of expertise) videos as well as a between-subjects comparison of segmentation and memory for basketball activities between basketball experts and novices. We predicted that basketball experts' segmentation ability and memory would be better for basketball videos compared to Overwatch, and that their segmentation and memory for basketball would be better compared to that of the novices. We also predicted that segmentation ability would predict memory for everyone, but that this relationship would be stronger for experts for the basketball videos.

Method

Participants

A total of 164 participants (69% female, *M* age = 18.80, *SD* = .10) were recruited from Kansas State University (KSU). Participants were recruited from the Department of Psychological Science's SONA participant pool, as well as from organizations across campus. Specifically, to increase recruitment of Overwatch experts, the study was advertised with the eSports Club at KSU. Participants were compensated with course credit or entered into a gift card raffle depending on the organization from which they were recruited.

Recruitment. In the first round of recruitment, participants completed an online pre-screen survey about basketball and Overwatch knowledge so that experts and novices in each area could be identified prior to returning for the lab-based study. Seven basketball experts (Overwatch novices) and 2 Overwatch experts (who unfortunately were not basketball novices) were recruited in this manner, such that they were identified as experts or novices prior to completing the lab-based experiment. Unfortunately, this method of recruitment yielded high attrition of experts who did not return to the lab-based segmentation experiment. Additionally, Overwatch experts were proving extremely difficult to find, despite the popularity of the game (Ranker, 2018). For these reasons, in the second round of recruitment, the survey and lab-based portions were combined into one session, thus opening the experiment up to individuals who would have been excluded based on their scores on the knowledge survey. This meant that the expert and novice groups for both activities were not identified until after data collection. This round of recruitment yielded 33 basketball experts (Overwatch novices), 12 Overwatch experts (3 of which were basketball novices, 9 of which had "intermediate" or expert basketball score), 59 controls (novices in both areas), and 53 "intermediate" individuals who scored above the novice but below the expert thresholds in either area. As stated previously, recruitment of Overwatch experts proved difficult, even after using the new recruitment method. Therefore, due to the low sample size, the main analyses of the current experiment exclude this group. For a visual depiction of the recruitment process, see Figure 1. For descriptive information on all expertise groups, see Table 4.

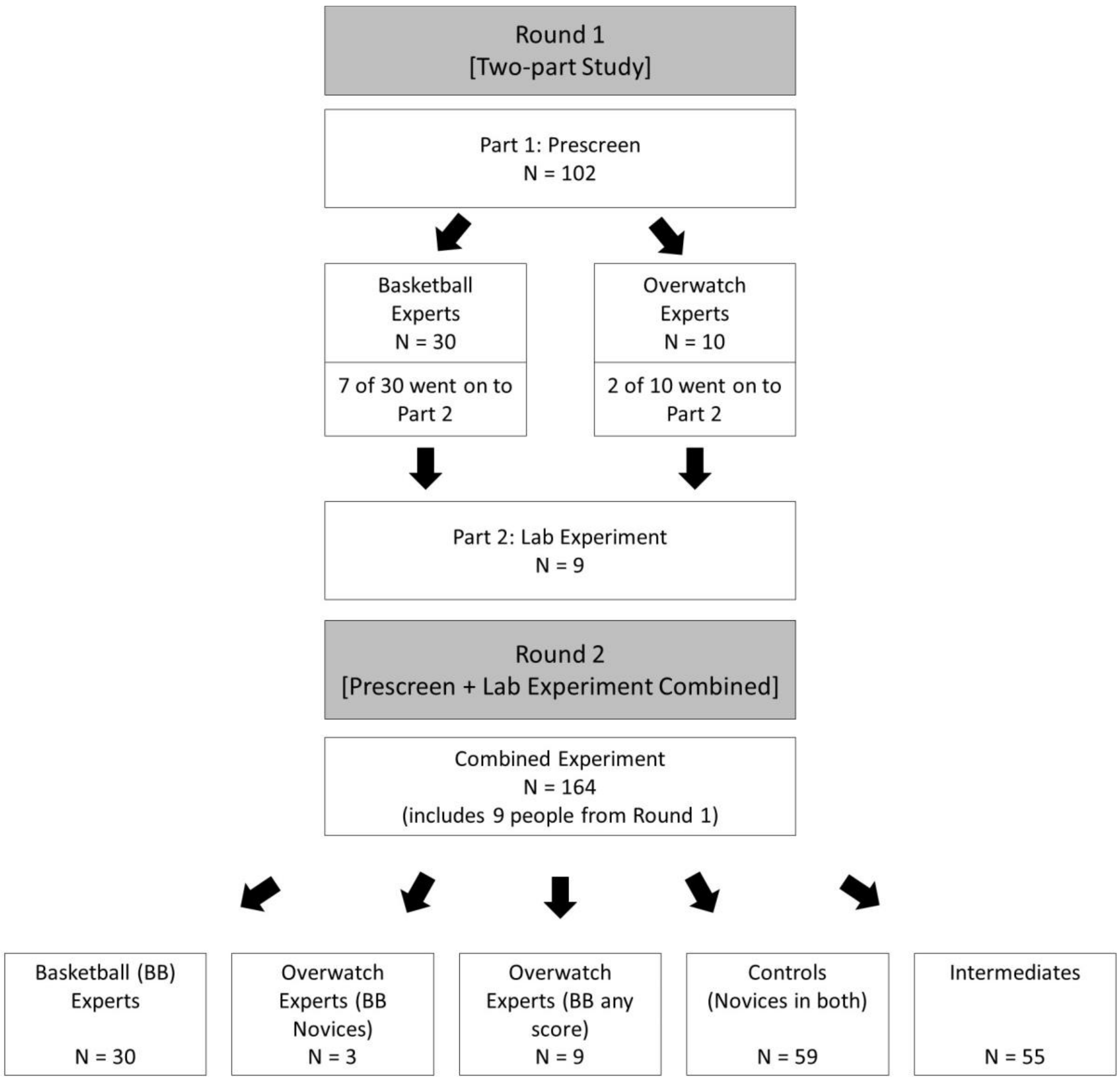


Figure 1. Flow-chart depicting recruitment process

Table 4. Demographic Information by Expertise Group

Demographic Information by Expertise Group

	Overall (N = 164)	Basketball Experts (N = 33)	Overwatch Experts (N = 12)	Controls (Novices) (N = 59)	Intermediates (N = 55)
Age					
M_{years}	18.80 (.10)	18.66 (.12)	18.75 (.33)	18.82 (.18)	18.82 (.19)
Education					
M_{years}	12.47 (.08)	12.23 (.09)	12.50 (.26)	12.60 (.16)	12.47 (.13)
Gender					
Female	113	18	0	55	40
Male	51	17	12	6	15
Race					
White	138	32	10	48	47
Black/African American	7	2	0	3	2
Asian	11	0	1	6	4
American Indian	6	1	1	3	1
Hispanic/Latino					
No	148	32	11	53	52
Yes	16	3	1	8	3

Note: Standard error in parentheses.

Materials

The survey, videos, segmentation, memory, and cognitive tasks used in this experiment are described in detail below.

Knowledge survey. As described in Experiment 1, knowledge surveys were used to identify experts and novices in 2 activities: basketball and Overwatch. The basketball portion of the survey was a modified version of Feller et al., (in prep, adapted from French & Thomas, 1987), such that it was reduced to 23 questions to match the Overwatch survey, which was developed (Experiment 1) for use in the current study. Both the basketball and Overwatch surveys included 23 questions each about general information regarding each activity as well as

7 self-report familiarity and expertise questions. All questions had 5 answer options, with the 5th option (e) always stating “I don’t know.” Both surveys are included in Appendix A.

Videos. Five videos were used in this experiment (1 practice; 4 experimental). The practice video depicted a man using Legos to build a ship (155 s). Two of the experimental videos were college basketball games; specifically, Memphis vs. UCLA (153 s) and Montana vs. Weber State (130; Feller et al., in prep). The other two experimental videos were Overwatch tournament matches; specifically, Houston vs. Boston (144 s) and London vs. Florida (135 s). The Overwatch videos were chosen because they were professionally recorded games played by Overwatch experts. Participants viewed all of the experimental videos twice (once per segmentation grain).

Unitization task. The unitization task (Newtson, 1973) was used as an overt measure of participants’ perception of event boundaries in each of the videos. While watching the videos, participants were asked to press the spacebar each time “one meaningful unit of activity ends and another begins.” Participants were shaped on this task using a practice video. Participants were instructed to identify larger or smaller units of meaningful activity by pressing the spacebar (Mann, Williams, Ward, & Janelle, 2007). Participants had to identify at least 3 larger (coarser) units or 6 smaller (finer) units in order to move on to the experimental trials. If this threshold was not met, participants received feedback stating that other individuals typically identify more units; however, they were not given explicit examples of how the activities in the video could be broken down into segments. After receiving this message, participants repeated the shaping procedure until they passed the threshold.

Distractor tasks. Four, 5-minute distractor tasks were used to reduce recency effects on the memory tasks. A demographics questionnaire was used as one of the filler tasks. The rest of the tasks were measures of different cognitive abilities.

Semantic knowledge. The following measures were used to assess individual differences in general knowledge.

Object naming test. Participants completed a computerized version of the object-naming task. They were presented with black and white drawings of objects from Snodgrass and Vanderwart (1980), one at a time, and were instructed to type out the name of each object into a text box. If they were not able to name the object, they had the option of clicking on one of three answer options which included "Don't Know Name," "Don't Know Object," and "Tip of Tongue." Participants were given 5 minutes to name as many pictures as possible. Participants were given 1 point for each correct response.

Shipley-Hartford vocabulary test. Participants were given 5 minutes to complete a computerized version of the synonyms vocabulary test (Salthouse, 1993). On each trial, a bolded, underlined (target) word was presented at the top of the screen. Five multiple-choice answers (A through E) were presented below the target word. Participants were asked to click on the letter of the answer option that was synonymous, or most close in meaning, to the target word. Participants were asked to complete this task as quickly and as accurately as possible and received 1 point for each correct answer.

Processing speed. The following measures were used to assess individual differences in processing speed.

Letter comparison (LC). Pairs of letter strings were presented on screen. Participants indicated with a button press whether the pairs of letters were the same or different. They were instructed to respond quickly and accurately to as many pairs as possible in 60 seconds. Letter strings consisted of randomly selected consonants and ranged in length from 3 to 9 letters (Salthouse & Babcock, 1991). Participants received 1 point for each correct response.

Pattern comparison (PC). Pairs of patterns were presented on screen, and participants indicated with a button press whether the pairs of patterns were the same or different. Again, they were asked to respond quickly and as accurately to as many pairs as possible in 60 seconds. The patterns were made of connected lines in an invisible 4 x 4 matrix, with 3, 6, or 9 line-segments in each member of the pair (Salthouse & Babcock, 1991). Participants received 1 point for each correct response.

Event memory measures. Two tasks were used to assess memory for the activities in each video.

Recognition. Recognition memory was assessed using a two-alternative forced-choice test (see Appendix A for example trial). There were 20 trials per video, each containing 1 target and 1 distractor image, presented side-by-side. Target images always came from the videos that participants watched, and distractor images always came from portions of the same video that participants did not see. Presentation order of the image pairs was the same for each participant. Participants received 1 point for each correctly identified image (up to 20 total points). Participants' scores were reported as total count.

Order memory. Order memory was assessed using a two-alternative forced-choice test (see Appendix A for example trial), based on the measure used by Dubrow & Davachi (2014). For each video, participants were presented with 8 image pairs on the computer. All the images came from the videos participants watched. A prompt appeared on screen stating, "more recent?" and participants were instructed to choose the image depicting the more recent action.

Participants received 1 point for each correctly identified image (up to 8 total points). Participants' scores were reported as total count.

Working memory task. Each participant's working memory ability was assessed.

Reading span (RSPAN). The RSPAN task required participants to recall letters while completing a secondary task of reading sentences (Bailey, 2012; Kane et al., 2004). Participants were presented with a sentence (e.g., "We were fifty lawns out at sea before we lost sight of land. ? K"), followed by a letter. They were given 4 seconds to indicate whether the sentence made sense or not, by choosing a "correct" or "incorrect" button with the computer mouse. After a decision was made, a letter appeared on screen for 1 second. This process repeated for an entire set. At the end of a set, participants saw a recall screen and were asked to type the letters in the order in which they were presented. Set sizes ranged from 3 to 7 sentence-letter problems per trial, for 15 trials total. Nonsense sentences were created by changing 1 word, which appeared equally often in the beginning, middle, and end of the sentences. Each sentence consisted of 10 to 15 words. For each trial, each participant received a proportion value, ranging from 0 to 1, (number of letters correctly recalled in order divided by the total number of to be recalled items for that trial). Next, each participant's proportion values were averaged across all 15 trials to obtain an overall proportion correct score.

Design and Procedure

Expertise was treated as a between-subjects variable such that participants ($N_{BasketballExperts} = 33$, $N_{ControlNovices} = 59$) were grouped based on their scores from the knowledge survey about basketball and Overwatch (novice ≤ 7; expert ≥ 17; Table 5). To be clear, all individuals in the basketball expert group were also novices in Overwatch, separate from individuals in the control group, who were identified as novices in both activities. Activity (basketball and Overwatch) was treated as within-subjects, such that all participants viewed and segmented videos of each activity. Participants were asked to segment each video twice: once per grain (Coarse vs. Fine). Video and distractor task were counterbalanced across participants. Segmentation grain was counterbalanced, such that participants segmented all the videos at one grain, then after completing the last block of tasks for the last video, they segmented all the videos again at the other grain, in the same order.

Table 5. Knowledge Scores by Expertise Group

Knowledge Scores by Expertise Group

	Basketball Experts	Controls (Novices)
Overwatch	1.29 (.38)	1.34 (.28)
Basketball	20.06 (.27)	4.51 (.29)

Note: Standard error in parentheses. Novice ≤ 7; Expert ≥ 17.

All participants (except nine participants from the first round of recruitment; see *Recruitment* section above) entered the lab in small groups of 3 or 4 and were seated at a computer. They first filled out an informed consent form and then completed the knowledge survey. After completing the survey, they were given a demographics form and instructed not to fill it out until the experimental program on the computer told them to do so. Each participant was then presented with the practice video, which shaped each participant's segmentation behavior and was tailored to whichever segmentation grain order each participant was assigned (i.e., at least 3 button presses for coarse grain; at least 6 for fine grain). Once each participant completed the shaping procedure, the experimental trials began. The experimental trials consisted of 4 blocks. In each block, the experimental video was presented, and participants were instructed to "press the spacebar any time they felt a meaningful unit of activity ended and a new one began." After each video, participants completed a distractor task, and then moved on to the recognition and order memory tasks. Memory task order was not counterbalanced because the viewing of target images in the order memory task could have aided participants on the recognition task. After the order memory task for the last video of the last block, participants were shown the practice video again and trained on the segmentation task for the alternative grain. Participants then re-segmented each video at this new grain in the same order in which the videos were originally presented. At the end of the experiment, participants completed the working memory task. Finally, they were debriefed, thanked, and compensated for their time (see Figure 2).

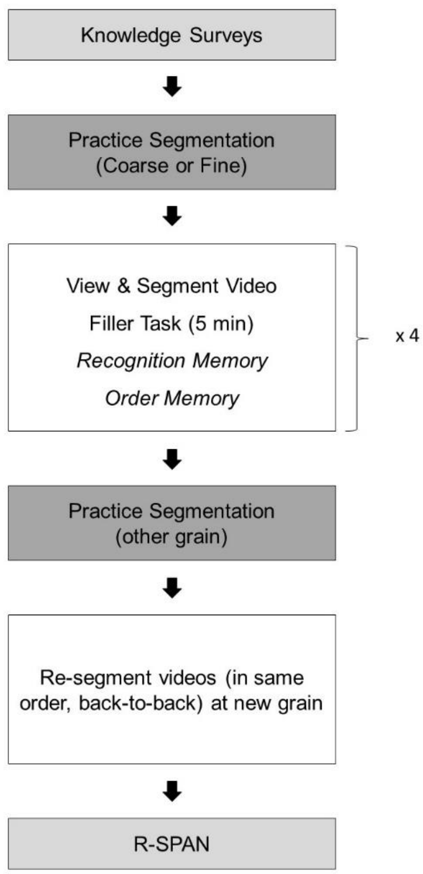


Figure 2. Flow-chart of Experiment 2 procedure

Results

Data Preparation

As stated previously, attrition and recruitment issues focused the analyses of the current experiment to basketball experts and control novices. No outliers were identified; however, all data from 8 participants were missing due to technological issues and therefore not included in any analyses.

Approach

The main analyses were conducted using generalized multilevel modeling techniques. These techniques were used to account for non-normal error distributions (e.g., Poisson for count data, logistic for binomial) of the various dependent measures, as well as error variance associated with random effects, such as inherent differences across individual participants and videos. To encourage convergence of the models, predictors such as recruitment phase, activity order, and grain order were not included in the models reported below; however, preliminary models including those variables indicated that none of those variables were significant predictors and they did not interact with any of the other variables (all $p > .05$). To ease comparisons, group means for the various measures are presented in tables corresponding to each section. All error bars indicate standard error of the mean and the colored areas surrounding lines of best fit indicate confidence of the fit of the line. We first assessed whether basketball experts and controls were similar in their general cognitive ability, in addition to how well each of the encoding and retrieval tasks correlated with measures of cognitive ability. We then evaluated encoding processes, including segmentation frequency, agreement, and hierarchical alignment, and then evaluated retrieval processes, including recognition and order memory. Next, we assessed the extent to which encoding predicted retrieval. Finally, we end with an exploratory section in which knowledge was treated as a continuous variable and all participants' (n = 164) data were used. Two tables summarizing all of the analyses and effects are provided at the end of the results section (Tables 11 and 12). Additionally, tables reporting task performance (knowledge, segmentation, and memory) differences for all groups can be found in Appendix B.

Cognitive Battery

Given that participants were not randomly assigned to groups, all participants completed a series of cognitive measures (processing speed, vocabulary, semantic knowledge, and working memory) to assess baseline differences between groups that may have otherwise explained any possible segmentation and memory effects. A series of t-tests confirmed that basketball experts and control novices did not differ on any of the cognitive measures (all $p > .05$; Table 6). Bayes factors of less than 1 also suggested substantial evidence for the null (i.e., no differences; Wetzels & Wagenmakers, 2012). This suggests that any significant effects found on segmentation and memory are most likely due to differences in knowledge for the two activities rather differences in some pre-existing cognitive ability. Relationships between measures of cognitive ability, encoding, and retrieval are provided in Table 7.

Table 6. Performance on Cognitive Battery

Performance on Cognitive Battery by Expertise Group

	Basketball Experts	Controls (Novices)	*t*	*p*	BF_{10}
Letter Comparison	16.38 (.38)	16.08 (.34)	0.56	0.58	0.26
Pattern Comparison	21.17 (.63)	20.28 (.60)	0.96	0.34	0.34
Object Naming	56.12 (1.45)	53.44 (1.47)	1.20	0.23	0.42
Vocabulary Knowledge	14.03 (.48)	13.48 (.49)	0.73	0.47	0.28
R-SPAN	0.80 (.02)	0.77 (.02)	1.08	0.28	0.39

Note: Standard error of the mean in parentheses. Letter comparison and pattern comparison were both measures of processing speed. Object naming and vocabulary were both measures of semantic knowledge. R-SPAN was a measure of working memory capacity. BF = Bayes Factor, evidence for the null.

Table 7. Cognitive Battery Correlations

Correlations between Cognitive Battery, Encoding, and Retrieval Measures for Basketball Experts and Control Novices

Measures		Cognitive Battery					Encoding						Retrieval	
		LC	PC	V	NT	R-SPAN	CSC	FSC	CSA	FSA	TD	E	R	OM
Cognitive Battery	Letter Comparison (LC)	1												
	Pattern Comparison (PC)	.42	1											
	Vocabulary (V)	.20	.12	1										
	Naming Test (NT)	.41	.39	.40	1									
	R-SPAN	.30	.23	.37	.39	1								
Encoding	Coarse Segmentation Count (CSC)	-.10	-.07	-.19	-.09	-.14	1							
	Fine Segmentation Count (FSC)	.13	.16	-.04	.16	.04	.59	1						
	Coarse Segmentation Agreement (CSA)	.23	.21	.11	.16	.17	-.10	.10	1					
	Fine Segmentation Agreement (FSA)	.17	.12	-.00	.10	.15	-.01	.02	.43	1				
	Temporal Distance (TD)	.19	.14	.12	.19	.10	-.16	-.08	.51	.42	1			
	Enclosure (E)	.09	.15	.16	.05	.21	-.21	.14	.34	.46	.36	1		
Retrieval	Recognition (R)	.24	.17	.19	.17	.16	-.04	.15	.26	.13	.16	.28	1	
	Order Memory (OM)	-.27	-.19	.08	-.23	-.17	-.01	-.05	-.01	-.02	-.02	-.03	.02	1

Encoding Measures

Unitization. Two measures of unitization were used to assess how well individuals identified and agreed on the locations of boundaries in each video.

Segmentation frequency. Segmentation frequency was scored as the total number of button presses (i.e., total number of perceived event boundaries) per video. Blasing (2015) found that experts identified fewer event boundaries compared to novices; therefore, we predicted a within-subjects difference such that basketball experts would segment less often, regardless of grain, during basketball videos, compared to Overwatch videos. We also expected to find a between-subjects difference such that basketball experts would segment less often compared to the control novices, for the basketball videos. Additionally, we expected participants to segment less often at the coarse grain compared to the fine grain, regardless of expert knowledge and activity.

To investigate these hypotheses, a generalized Poisson multilevel model was used to predict segmentation frequency from the full factorial of the fixed effects of group (experts vs. control novices), activity, and segmentation grain, and the random effects of participant and video (Table 7; Figure 3). A significant main effect of grain was present ($z = -49.63$, $p < .001$) such that everyone identified fewer coarse boundaries than fine boundaries, regardless of knowledge or activity. The main effects of group and activity were not significant, indicating that there were no baseline differences in the number of perceived events between groups or between activities; however, these fixed effects did interact with grain. A significant 2-way interaction between group and grain was present ($z = -11.11$, $p < .001$) such that control novices identified fewer fine boundaries compared to basketball experts, regardless of activity, but no group differences were present at the coarse grain. These results were qualified by a significant 3-way interaction between group, activity, and segmentation grain (z = -3.17, p = .002), such that participants identified significantly more fine boundaries than coarse boundaries for the basketball videos, compared to Overwatch, and this difference was greater for basketball experts compared to control novices. No other effects were present (all $p > .05$).

These results did not support our conceptual hypothesis in the way it was presented, such that experts would segment less often compared to novices, particularly for activities in their field of expertise. Instead, results suggest that experts and novices identified a similar number of coarse boundaries, regardless of activity, and that experts identified *more* fine boundaries for activities within their field of expertise, which supports the differentiation hypothesis.

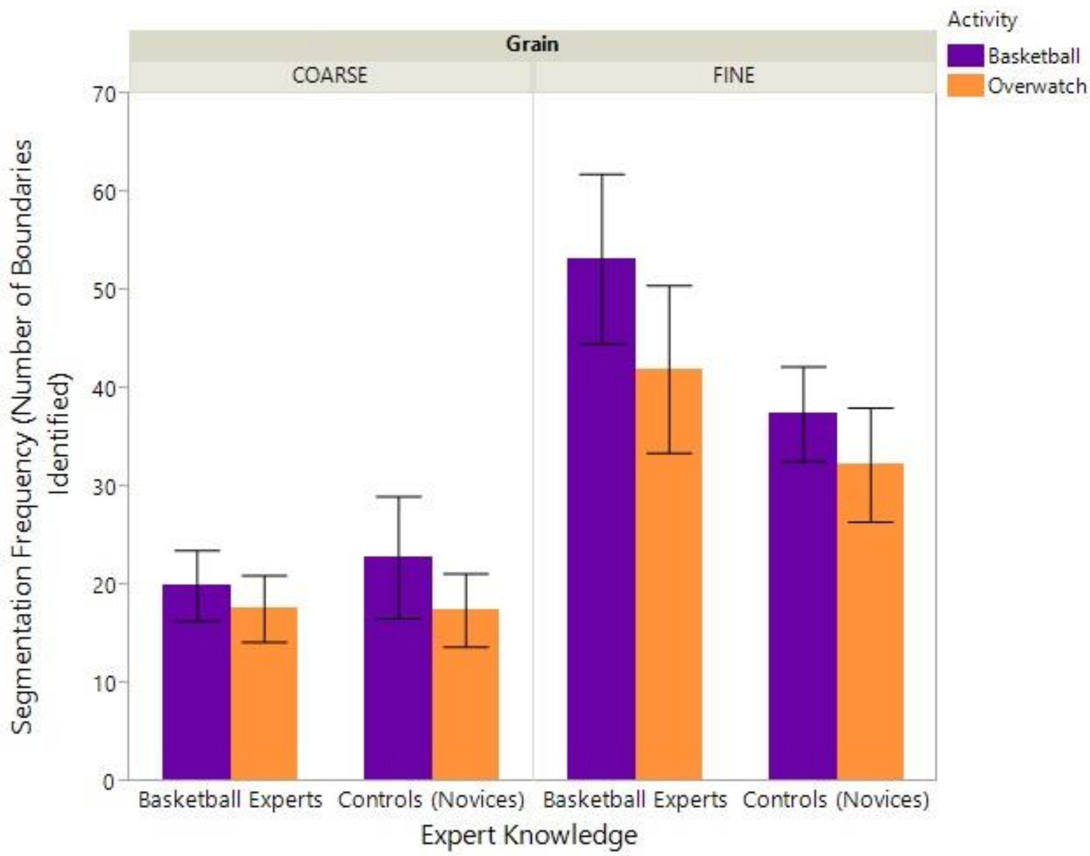


Figure 3. Number of boundaries identified for each activity.

Segmentation agreement. Segmentation agreement refers to how well individuals agree with others on the locations of perceived event boundaries. Higher segmentation agreement corresponds to more normative segmentation. To calculate agreement, each participant's segmentation data was smoothed by fitting a Gaussian kernel density function around each event boundary (button press), for each video. Each frame of each video received a value ranging from 0 to 1, indicating the probability or likelihood that the frame was an event boundary. A bandwidth of 25 (i.e., 25 frames per second) was used to correspond to 1 second time bins, such that frames closer to where the participant identified an event boundary received a larger value, compared to frames farther away. Next, the probability associated with each frame or button press was averaged across participants to create normative event boundaries. Finally, each participant's segmentation probability at each frame was correlated with the normative boundaries[1]. Based on Levine et al. (2017), we predicted a significant between-subjects effect such that basketball experts' segmentation agreement would be higher than novices' for basketball videos compared to Overwatch videos, regardless of grain. However, we also expected to observe a within-subjects effect such that basketball experts' segmentation agreement would be higher for basketball videos compared to Overwatch videos, regardless of grain.

To evaluate these hypotheses, a generalized linear multilevel model was used to predict segmentation agreement from the full factorial of the fixed effects of group, activity, and

---

[1] Each participant received 1 correlation score for each of the 8 videos (i.e., 4 videos x 2 grains). This entire process was repeated 3 times, using everyone, domain experts, and one's own group as the different comparison groups for generating the normative boundaries. The main analyses presented used everyone as the comparison (normative) group to increase power; however, results based on segmentation agreement scores using the other comparison groups can be found in Appendix B.

segmentation grain, and the random effects of participant and video (Table 8; Figure 4). A significant main effect of grain was present ($t = -4.05$, $p < .001$) such that agreement of fine

Table 8. Segmentation Ability by Expertise Group

Segmentation Ability by Expertise Group

	Activity	Video	Grain	Segmentation Count	Segmentation Agreement (Everyone)
Basketball Experts					
	Overwatch	HOUvBOS	Coarse	16.81 (2.27)	.28 (.02)
			Fine	41.64 (6.41)	.34 (.03)
		LONvFLA	Coarse	18.36 (2.61)	.16 (.02)
			Fine	42.36 (5.75)	.19 (.02)
	Basketball	MEMvUCLA	Coarse	23.33 (2.77)	.35 (.03)
			Fine	59.30 (6.45)	.37 (.04)
		MTvWS	Coarse	16.58 (2.16)	.37 (.03)
			Fine	47.09 (5.66)	.39 (.04)
Controls (Novices)					
	Overwatch	HOUvBOS	Coarse	17.80 (2.85)	.27 (.02)
			Fine	29.84 (3.45)	.31 (.02)
		LONvFLA	Coarse	17.12 (2.47)	.14 (.02)
			Fine	34.71 (4.76)	.14 (.01)
	Basketball	MEMvUCLA	Coarse	28.64 (5.94)	.28 (.02)
			Fine	39.96 (3.65)	.38 (.03)
		MTvWS	Coarse	17.24 (2.10)	.30 (.02)
			Fine	34.89 (3.24)	.40 (.03)

Note: Standard error in parentheses.

boundaries was higher than agreement of coarse boundaries. However, this effect was qualified by a significant 3-way interaction between group, activity, and grain ($t = 2.29$, $p = .02$). All participants showed higher agreement for the basketball videos ($M = .35$; $SE = .01$) compared to the Overwatch videos ($M = .22$; $SE = .01$), but experts ($M = .36$; $SE = .02$) showed a significantly larger effect than did the novices ($M = .29$; $SE = .02$), only at the coarse grain. The within-subjects effect ($d = .96$) was larger than the between-subjects effect ($d = .42$). No other effects were significant (all $p > .05$).

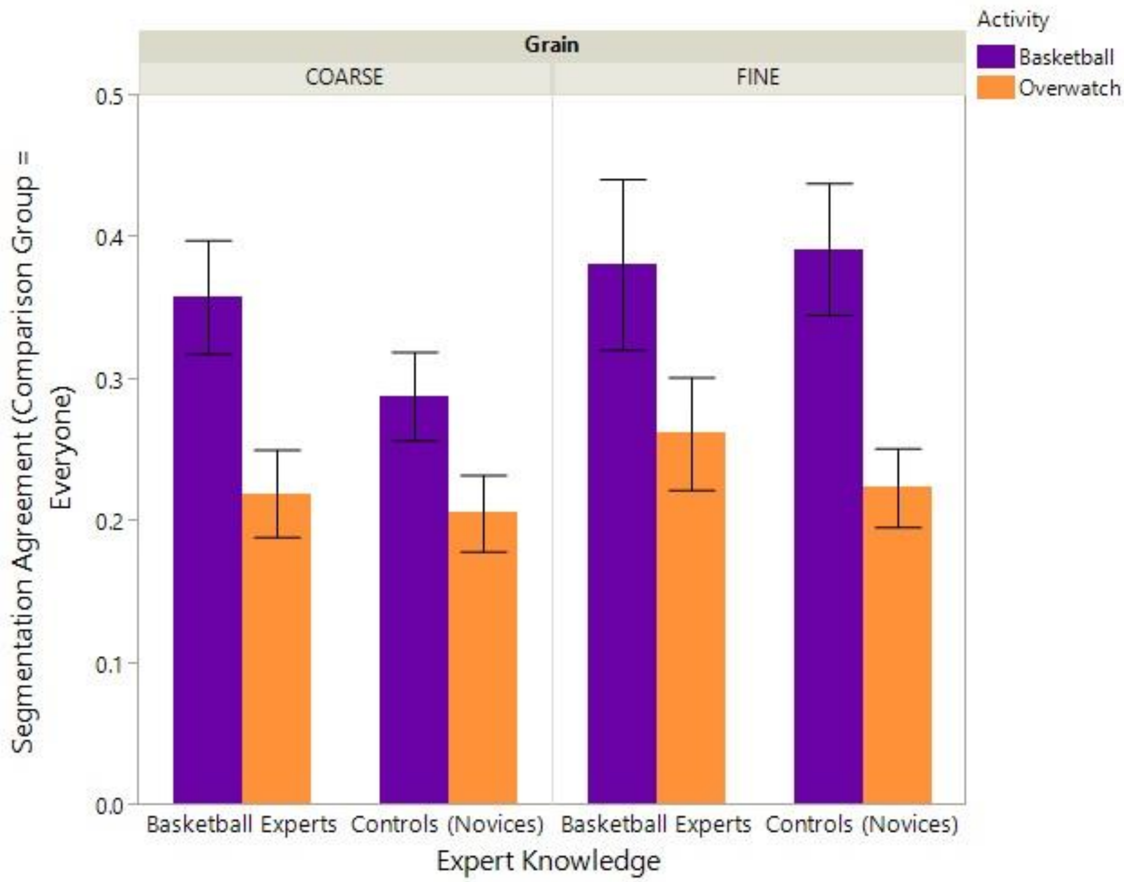


Figure 4. Segmentation agreement for each activity

These results partially support our hypothesis in that experts showed better segmentation agreement, compared to control novices, for activities within their expert domain, but only at the coarse grain. However, recall that experts did not identify significantly more coarse boundaries than control novices (see Figure 3). Altogether, this suggests that experts' better coarse segmentation agreement was not due to identifying *more* coarse boundaries, but rather identifying *more similar* coarse boundaries likely due to their shared knowledge for basketball.

Hierarchical alignment. Hierarchical alignment is the extent to which each identified coarse boundary temporally corresponds with an identified fine boundary (Kurby & Zacks, 2011; Sargent et al., 2013; Zacks et al., 2001). It is a measure of the encoding structure or organization of one's segmentation, or the degree to which each participant's coarse events comprise groups of related fine events (Sargent et al., 2013). Alignment was calculated in two ways: Temporal distance and Enclosure (described below). Across both measures, we predicted a between-subjects effect such that basketball experts, compared to control novices, would exhibit better alignment of coarse and fine boundaries for basketball videos, compared to Overwatch. We also predicted a within-subjects effect such that basketball experts themselves would exhibit better alignment of coarse and fine boundaries for basketball videos, compared to Overwatch, since they themselves were novices in Overwatch.

Temporal distance. For each coarse boundary, the temporal distance to the closest fine boundary was calculated, for each video, for each participant (Sargent et al., 2013). All of the temporal distances were then averaged within participants for each video and adjusted for expected average distance due to chance given the number of coarse and fine boundaries participants identified. Based on this calculation, higher scores mean "further from chance" and thus are better than lower scores. A generalized linear multilevel model was used to predict temporal distance from the fixed effects of group, activity, and their interaction, and the random effects of participant and video. A significant main effect of activity was present ($t = 3.99$, $p = .05$), such that temporal distance alignment of coarse and fine boundaries was better for basketball compared to Overwatch (Table 9; Figure 5). No other effects were significant (all $p > .05$). This result does not support our hypothesis and instead suggests that the structure of basketball may be inherently easier to identify than the structure of Overwatch, or that basketball is a more hierarchically organized activity than is Overwatch.

Table 9. Hierarchical Alignment by Expertise Group

Hierarchical Alignment by Expertise Group

	Activity	Video	Temporal Distance	Enclosure
Basketball Experts				
	Overwatch	HOUvBOS	.11 (.04)	.47 (.18)
		LONvFLA	.12 (.03)	.47 (.19)
	Basketball	MEMvUCLA	.22 (.03)	.56 (.03)
		MTvWS	.26 (.04)	.57 (.04)
Controls (Novices)				
	Overwatch	HOUvBOS	.11 (.04)	.41 (.03)
		LONvFLA	.05 (.03)	.45 (.03)
	Basketball	MEMvUCLA	.23 (.03)	.45 (.03)
		MTvWS	.31 (.04)	.49 (.03)

Note: Means are presented in the table and standard error in parentheses.

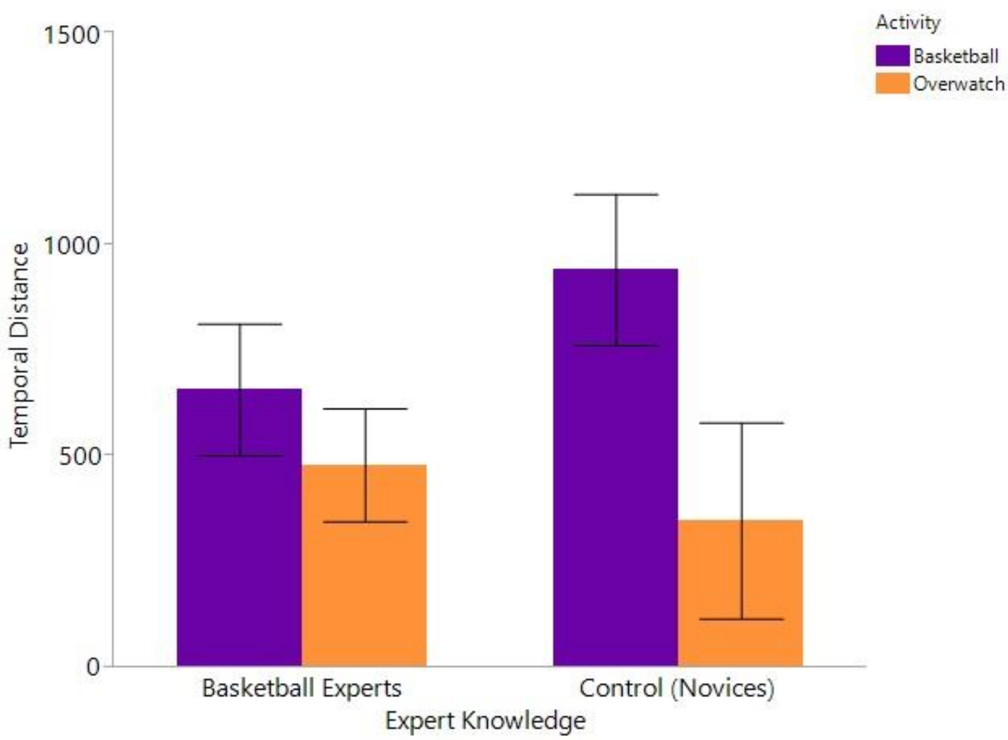


Figure 5. Temporal distance scores for each activity

Enclosure. Enclosure refers to the degree to which groups of related fine events are enclosed, or contained, within coarse events (Hard et al., 2011; Sargent et al., 2013). Each participant's coarse boundaries were scored based on whether they followed or preceded the closest fine boundary, for each video. Each participant's enclosure score was then the proportion of coarse boundaries that followed (rather than preceded) the closest fine boundary, accounting for expected enclosure due to chance. Again, higher values indicate better alignment. A generalized linear multilevel model was used to predict enclosure from the fixed effects of group, activity, and their interaction, and the random effects of participant and video. A significant main effect of group ($t = 2.07$, $p = .04$) and a marginally significant main effect of activity ($t = 3.27$, $p = .07$) were present; however, these effects were qualified by a significant interaction between group and activity ($t = 2.03$, $p = .04$). Basketball experts exhibited better enclosure for basketball compared to Overwatch, whereas control novices did not differ in their enclosure ability across the two activities (Table 9; Figure 6). This result supports our hypothesis in that experts showed better encoding organization of activities within their expert domain, when measured as enclosure.

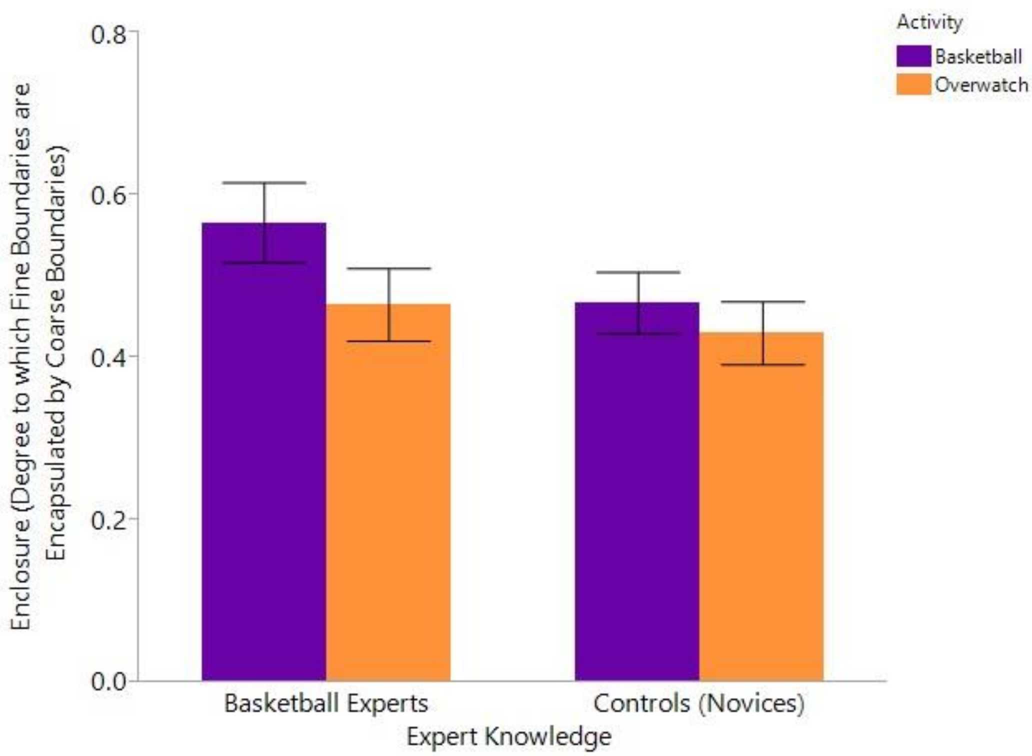


Figure 6. Enclosure scores for each activity

Retrieval Measures

Memory ability was assessed using two different measures: recognition and order. The majority of work done with experts has shown that experts possess better memory for information within their field of expertise (for review, see Ericsson & Smith, 1991). Based on this, we hypothesized to find a within-subjects effect such that basketball experts would exhibit better recognition and order memory for basketball videos compared to Overwatch videos. We also hypothesized to find a group x activity interaction such that experts would remember more than control novices for the basketball videos, but they would not differ in their recognition and order memory performance for the Overwatch videos.

Recognition. A generalized logistic multilevel model was used to predict recognition performance from the fixed effects of group, activity, and their interaction, and the random effects of participant and video. A significant interaction between group and activity was present (z = 5.05, p < .001) such that basketball experts exhibited significantly better recognition performance for basketball, compared to Overwatch, whereas control novices did not differ in their recognition performance across activities (Table 10; Figure 7). No other effects were present (all p > .05). This result supports our expertise hypothesis and replicates the benefit effect of expertise on memory for information in one's expert domain.

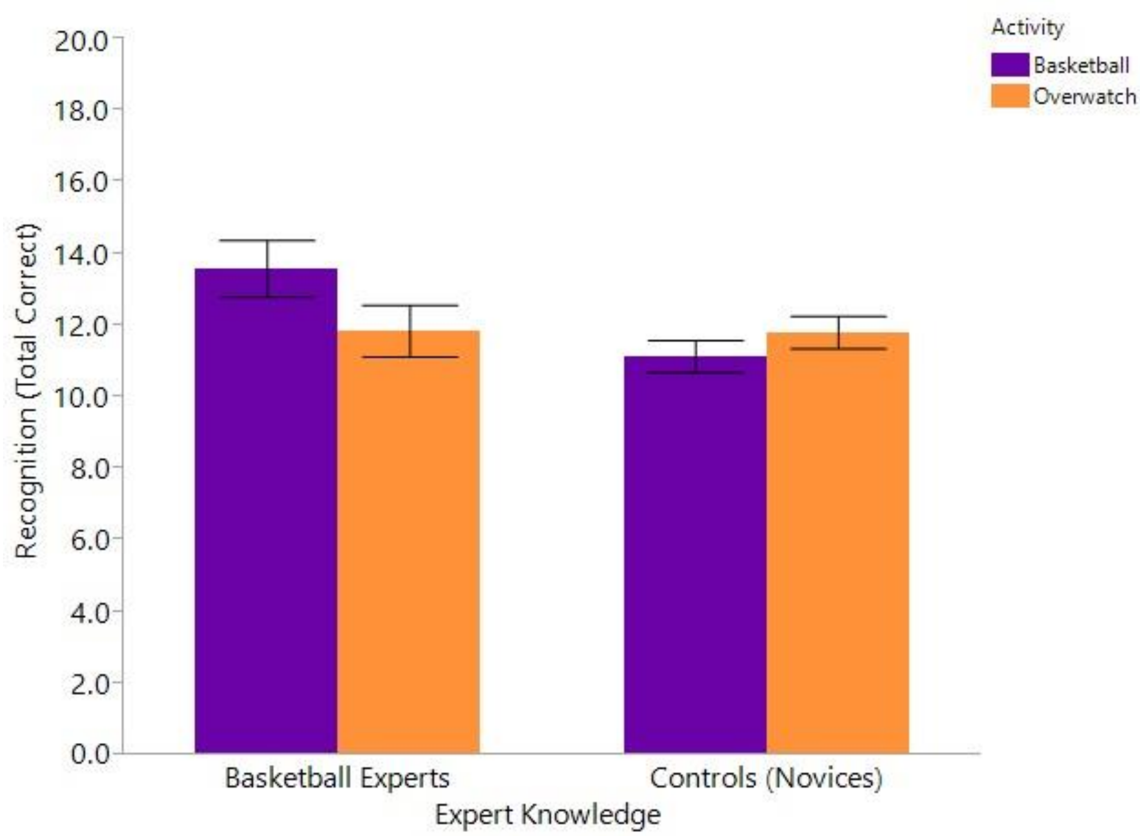


Figure 7. Recognition performance for each activity

Table 10. Average Memory Performance by Expertise Group

Average Memory Performance by Expertise Group

	Activity	Video	Recognition	Order
Basketball Experts				
	Overwatch	HOUvBOS	11.68 (.52)	4.41 (.26)
		LONvFLA	12.03 (.51)	4.41 (.27)
	Basketball	MEMvUCLA	12.53 (.51)	3.94 (.22)
		MTvWS	14.65 (.55)	4.21 (.28)
Controls (Novices)				
	Overwatch	HOUvBOS	11.00 (.30)	4.58 (.18)
		LONvFLA	12.62 (.31)	4.33 (.17)
	Basketball	MEMvUCLA	10.57 (.23)	4.35 (.18)
		MTvWS	11.72 (.38)	3.95 (.23)

Note: Means reported with standard error in parentheses.

Order memory. A generalized logistic multilevel model was used to predict order memory performance from the fixed effects of group, activity, and their interaction, and the random effects of participant and video. A significant main effect of activity was present ($z = -2.08$, $p = .04$) such that order memory was better for Overwatch, regardless of knowledge for the activity (Table 10; Figure 8). However, this effect should be interpreted with caution because it was likely the result of an overpowered analysis. Additionally, everyone performed close to chance (chance = 4/8), which suggests that either the task instructions were not clear or the task itself was extremely difficult. A Cronbach's alpha of .22 indicated that the internal consistency of this task was poor. For these reasons, any following analyses involving memory only include the recognition data. No other effects for order memory were present (all $p > .05$).

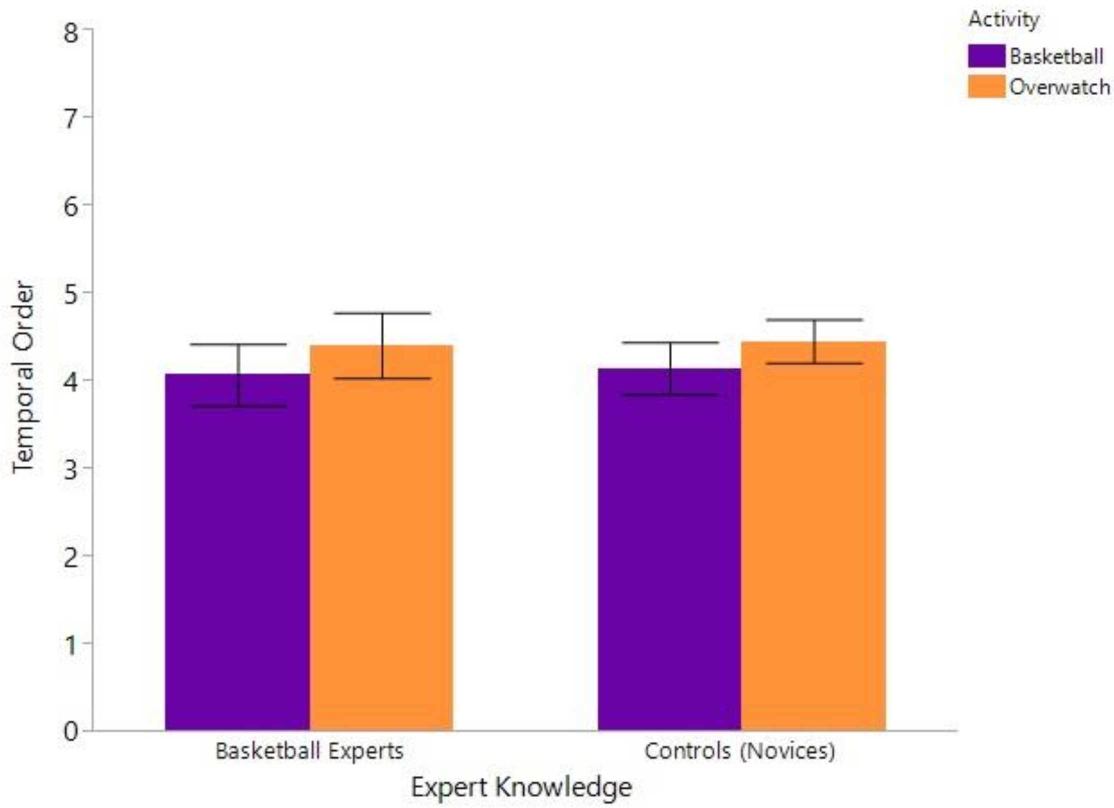


Figure 8. Order memory performance for each activity

Segmentation and Memory

Prior work has shown a positive relationship between segmentation agreement and memory for events (e.g., Bailey et al., 2013; Flores et al., 2017; Sargent et al., 2013). In the current experiment, we hypothesized that segmentation agreement would predict memory, such that basketball experts and control novices with higher agreement would also have better memory, regardless of activity. Additionally, we predicted that segmentation agreement would interact with group such that basketball experts would show an even stronger relationship between agreement and memory as compared to the novices for basketball videos. This prediction is based on the idea that knowledge would improve segmentation agreement, which would in turn improve memory.

Coarse segmentation agreement. A generalized Poisson multilevel model was used to predict recognition performance from the full factorial of the fixed effects of coarse segmentation agreement, group, and activity and the random effects of participant and video. A significant main effect of coarse segmentation agreement ($z = 1.96$, $p = .05$) indicated that recognition was indeed better for individuals with higher coarse segmentation agreement. A significant 2-way interaction between knowledge and activity was present ($z = -2.97$, $p = .003$), such that basketball experts' recognition was better for basketball videos, compared to Overwatch but novices' recognition did not differ by activity. A significant 2-way interaction between coarse segmentation agreement and activity ($z = -2.23$, $p = .03$) indicated that segmentation agreement more strongly predicted recognition for Overwatch than for basketball. Most interestingly, a 3-way interaction between segmentation agreement, group, and activity was marginally significant ($z = 1.90$, $p = .06$). Segmentation agreement only predicted recognition performance for those in the expert group and only for the Overwatch videos (Figure 9). No other effects were present (all $p > .05$).

These results partially supported our segmentation benefit hypothesis in that we predicted segmentation agreement would be associated with better memory; however, this relationship was not stronger overall for experts. In fact, experts' segmentation agreement did not explain their improved memory performance in their expert domain. Rather experts' segmentation agreement only predicted their memory performance for the *unfamiliar* activity, providing some initial support for the poor-get-richer hypothesis, suggesting that segmentation may benefit memory more when individuals need to rely on encoding efficiency and not semantic knowledge for an activity.

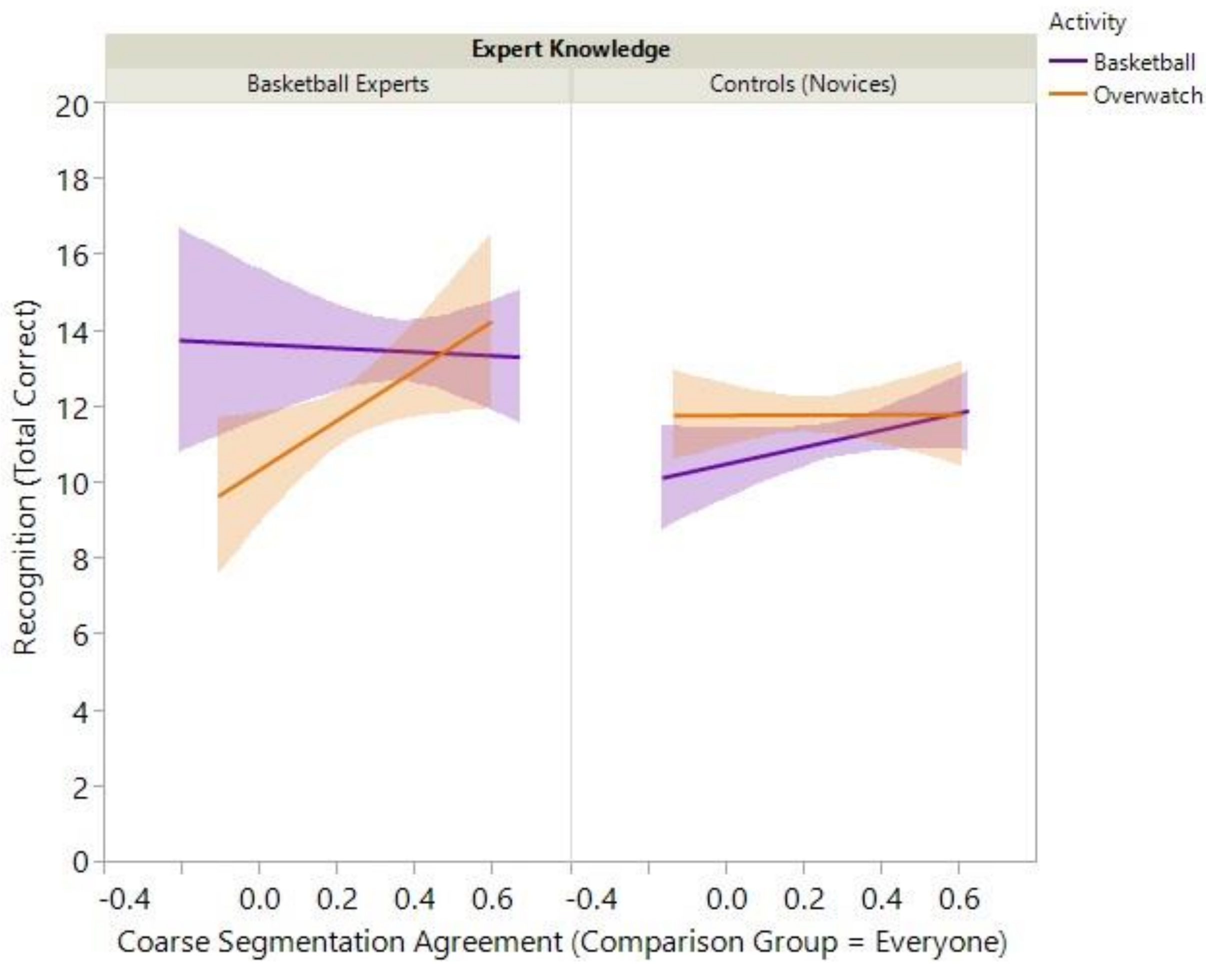


Figure 9. Coarse segmentation agreement predicting recognition performance

Fine segmentation agreement. A generalized Poisson multilevel model was used to predict recognition performance from the full factorial of the fixed effects of fine segmentation agreement, group, and activity and the random effects of participant and video. Significant 2-way interactions between group and activity (z = -3.26, p = .001) as well as activity and fine segmentation agreement (z = -2.31, p = .02) were found using fine segmentation agreement, replicating the effects found using coarse segmentation agreement above. Additionally, the same 3-way interaction of segmentation agreement, group, and activity on recognition was found here (z = 1.87, p = .06; Figure 10). No other effects were present (all p > .05). Similar conclusions drawn from the coarse segmentation agreement analysis were drawn here and are discussed in the general discussion.

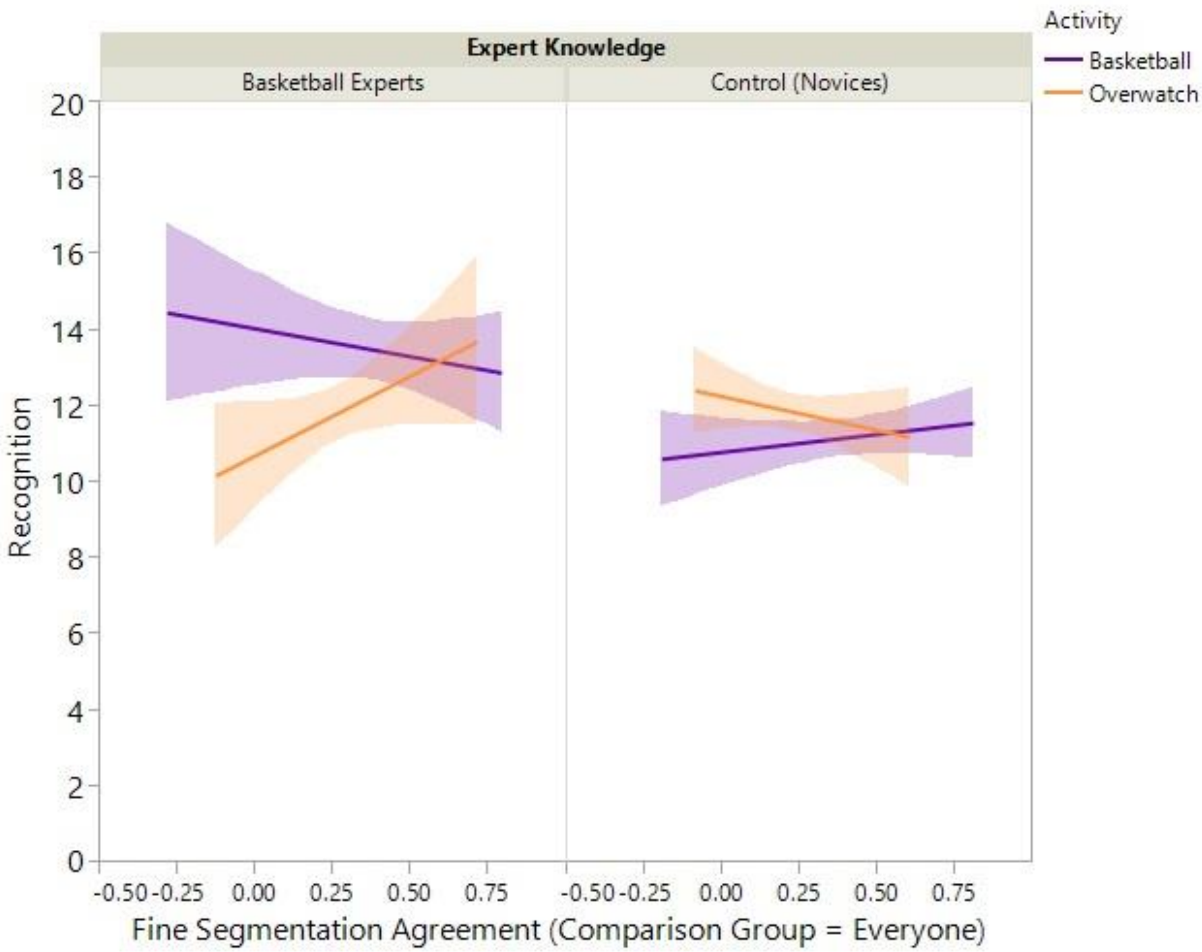


Figure 10. Fine segmentation agreement predicting recognition performance

Hierarchical alignment and memory. Like the set of analyses reported in the Segmentation and Memory section above, we conducted another set of analyses evaluating the influence of hierarchical alignment on recognition memory. Since alignment differences were only found when measured as enclosure (Encoding section above), we report only those analyses here. A generalized Poisson multilevel model was used to predict recognition performance from the full factorial of the fixed effects of enclosure, group, and activity and the random effects of participant and video. A marginal main effect of enclosure (t = 1.77, p = .08) suggests that better enclosure may be related to better memory. However, none of the effects were significant (all p > .05). Figure 11 depicts a pattern very similar to that found when using segmentation agreement to predict recognition (see Figures 9 and 10 above), cautiously suggesting that, in some cases, encoding efficiency may be important for memory when knowledge is lacking. However, this conclusion must be tentatively inferred, as the novices had no knowledge for basketball but agreement and enclosure did not predict memory.

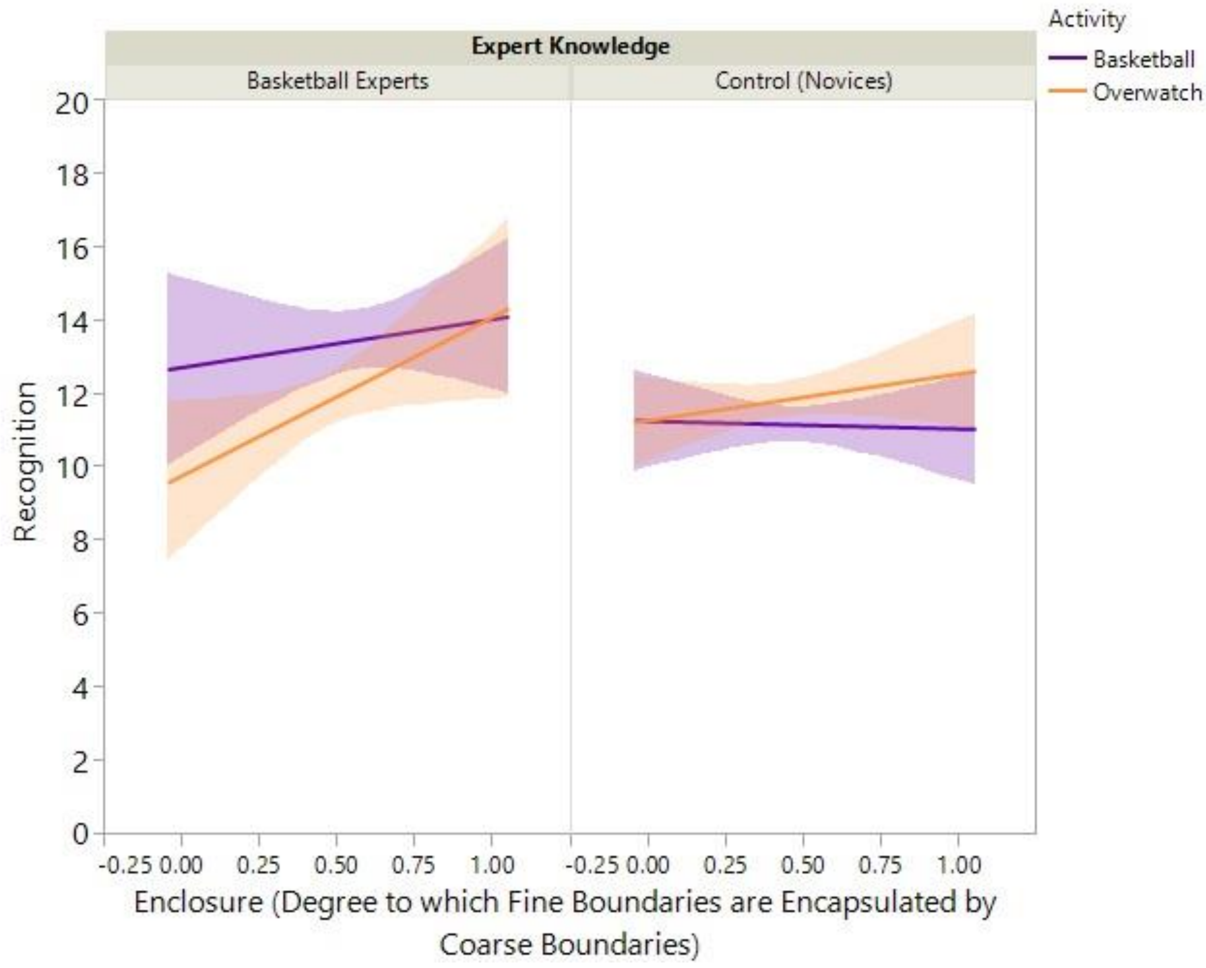


Figure 11. Enclosure predicting recognition performance

Exploratory Analyses

The exploratory analyses presented in this section included all participants' data (N = 164). For the following analyses, knowledge was treated as a continuous variable, using participants' scores earned on their basketball and Overwatch surveys. Results are organized in the same way as above (encoding measures, retrieval measures and then encoding predicting retrieval), and we made the same predictions as stated above.

Segmentation frequency. A general Poisson regression was used to predict segmentation count from the full factorial of the fixed effects of knowledge score, activity, and segmentation grain (Figure 12). Random effects were not included because the model would not converge (i.e., too complex). Significant main effects of knowledge score (z = 14.41, p < .001), activity (z = 5.70, p < .001), and grain (z = 14.57, p < .001) were present. A significant 2-way interaction between knowledge and activity (z = 7.55, p < .001) was present, such that more boundaries were identified for basketball, but not for Overwatch, as knowledge increased. A significant 2-way interaction between knowledge and grain (z = 19.35, p < .001) was present, such that more boundaries were identified at the fine, but not coarse, grain as knowledge increased. Additionally, a significant 2-way interaction between activity and grain (z = -10.15, p < .001) was present, such that more boundaries were identified at the fine grain for basketball, but not for Overwatch. However, the 3-way interaction between knowledge, activity, and grain was not significant (z = 1.61, p = .11).

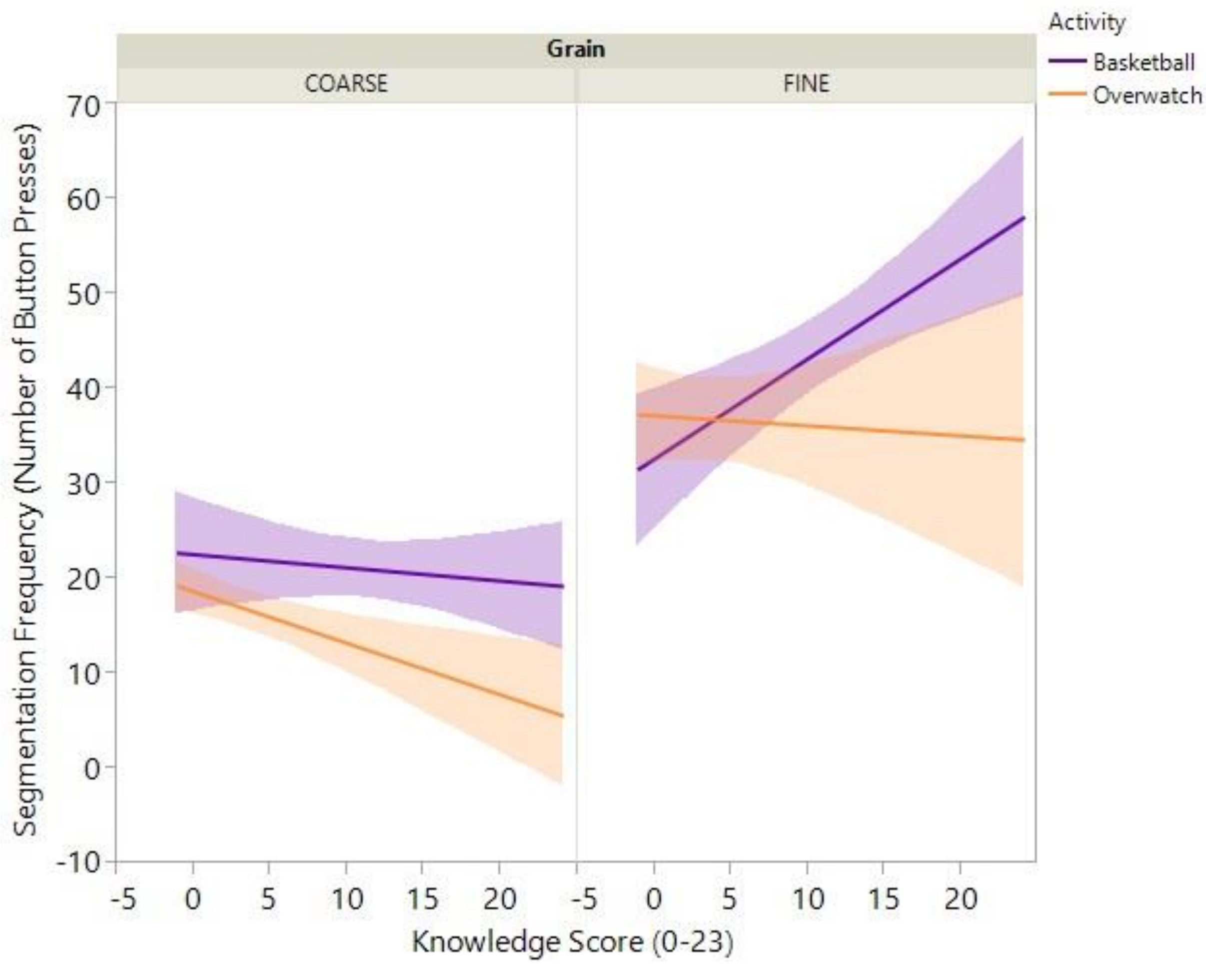


Figure 12. Exploratory Analysis: Number of boundaries identified by activity

Segmentation agreement. A generalized linear multilevel model was used to predict segmentation agreement (scored using everyone as the comparison group) from the full factorial of the fixed effects of knowledge score, activity, and grain and the random effects of participant and video (Figure 13). A significant main effect of grain was present ($t = -6.13$, $p < .001$) such that segmentation agreement of fine boundaries was better than segmentation agreement of coarse boundaries. A significant 2-way interaction between knowledge and activity was present ($t = 2.53$, $p = .01$), but these effects were qualified by a significant 3-way interaction between knowledge, activity, and grain (t = 3.22, p = .001). Fine segmentation agreement did not differ across levels of knowledge or activity, but coarse segmentation agreement did differ, such that agreement for basketball increased as knowledge increased and agreement decreased for Overwatch as knowledge increased. No other effects were present (all p > .05). These results suggest that more knowledge is associated with more normative segmentation agreement at the coarse grain, and replicates the effect found using separate expert and novice groups in the main analyses above, as well as previous work (e.g., Levine et al., 2017).

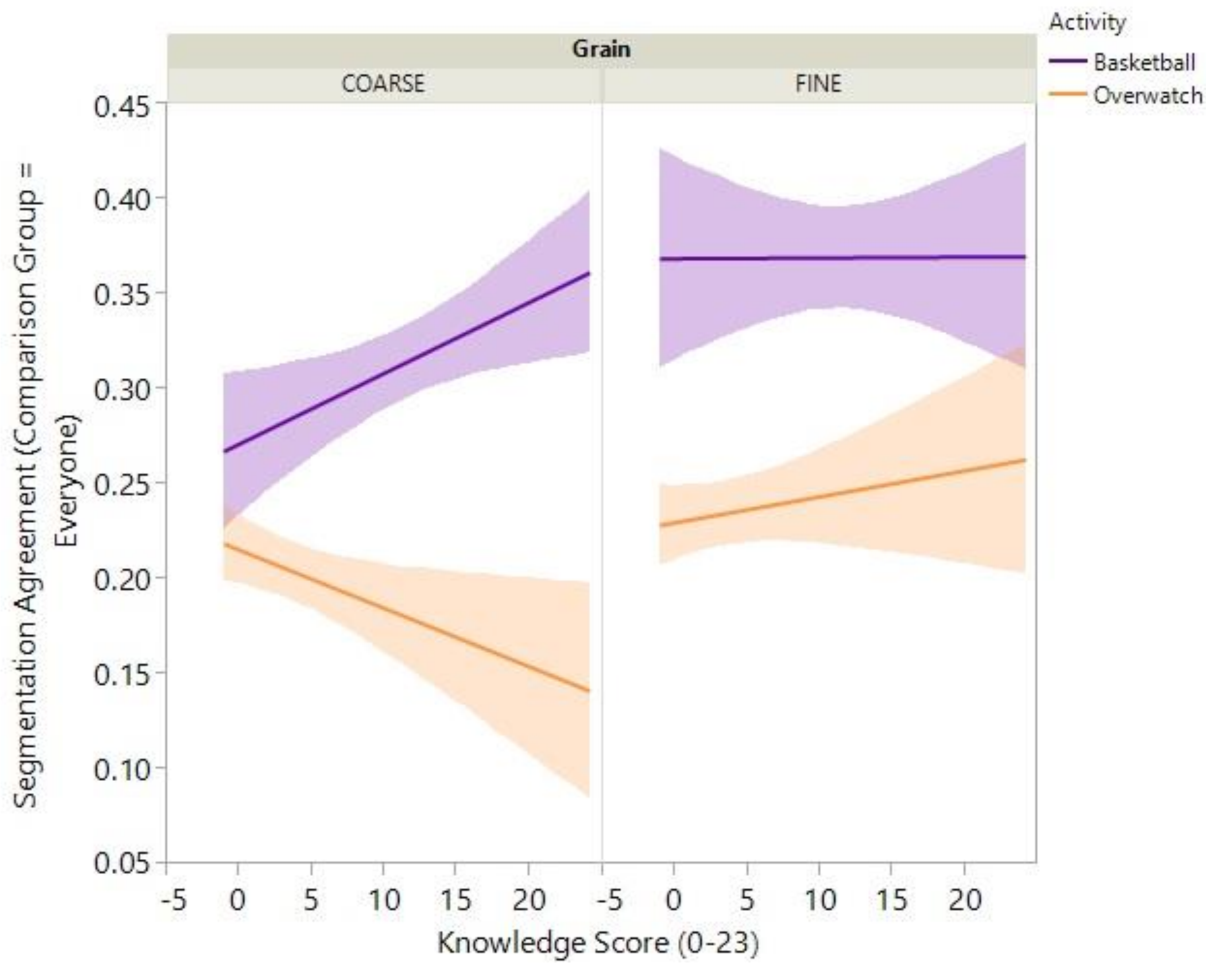


Figure 13. Exploratory Analysis: Segmentation agreement

Hierarchical alignment. Both measures of hierarchical alignment (temporal distance and enclosure) were evaluated.

Temporal distance. A generalized linear multilevel model was used to predict temporal distance alignment from the fixed effects of knowledge, activity, and their interaction, and the random effects of participant and video (Figure 14). A marginally significant main effect of activity was present ($t = 3.24$, $p = .05$) such that alignment was better for basketball videos compared to Overwatch, regardless of knowledge for the activity. The main effect of knowledge was not significant ($p = .25$). However, a significant interaction between knowledge and activity was present ($t = -2.14$, $p = .03$) such that alignment did not improve as knowledge for basketball increased but alignment did improve as knowledge for Overwatch increased. This result suggests that basketball may have been perceived as inherently more structured (replicating effects of enclosure in the main analyses) and knowledge was helpful in identifying event structure for Overwatch.

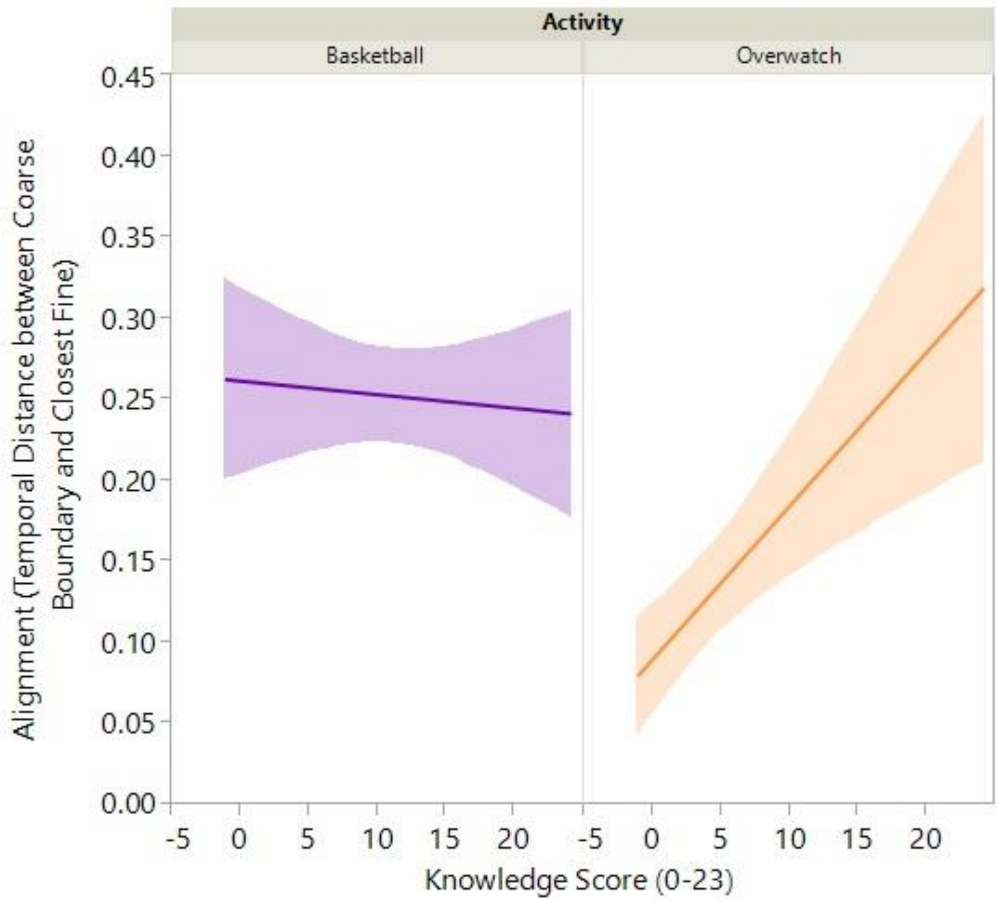


Figure 14. Exploratory Analysis: Knowledge predicting temporal distance

Enclosure. A generalized linear multilevel model was used to predict enclosure from the fixed effects of knowledge, activity, and their interaction, and the random effects of participant and video (Figure 15). This time, a significant main effect of knowledge was present ($t = 2.52$, $p = .01$) such that enclosure increased as knowledge increased, but the main effect of activity was not significant ($p = .31$). However, a significant interaction between knowledge and activity was present ($t = 2.33$, $p = .02$) such that knowledge predicted enclosure more so for basketball than for Overwatch. In contrast to the effects found using temporal distance, this result suggests that knowledge was associated with better identification of event structure, but this relationship was stronger for basketball.

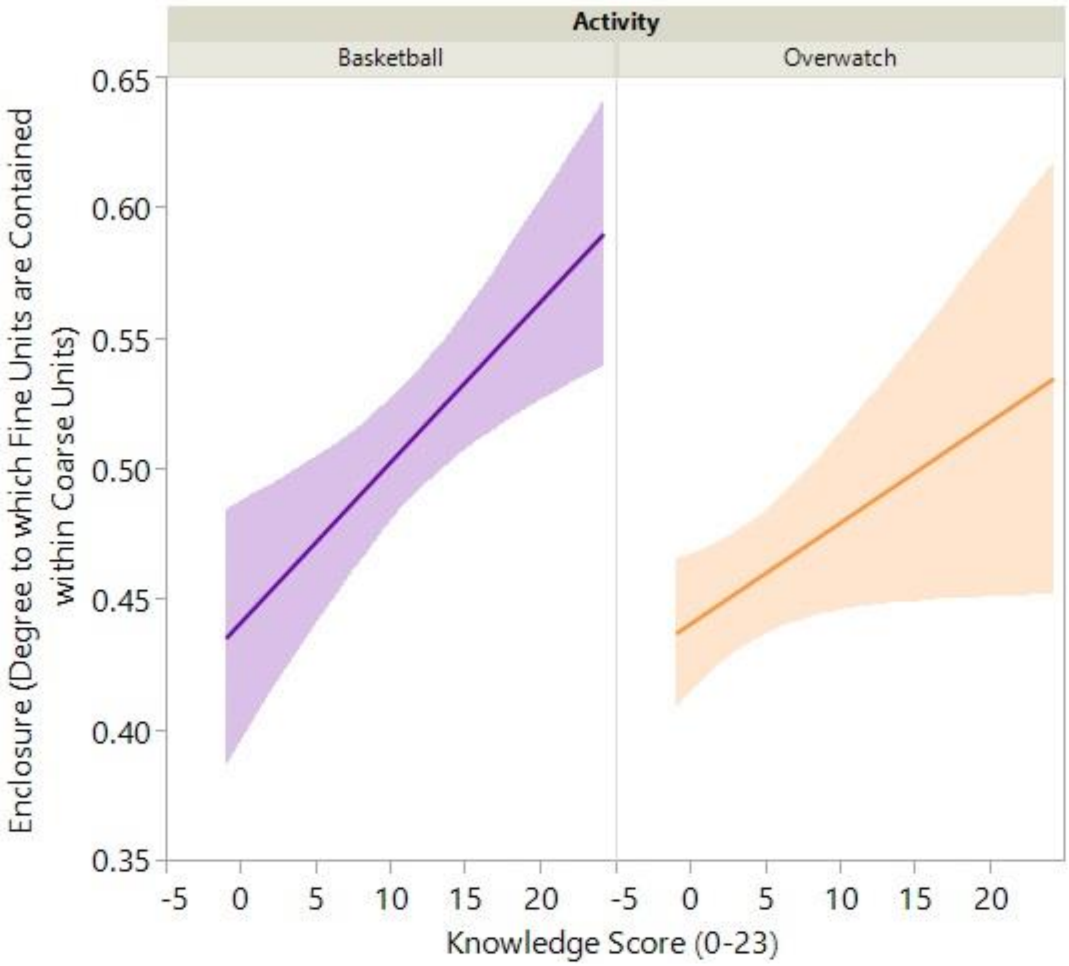


Figure 15. Exploratory Analysis: Knowledge predicting enclosure

Memory. As mentioned above, because the order memory test showed extremely poor internal consistency, only recognition performance was evaluated.

Recognition. A generalized Poisson multilevel model was used to predict recognition performance from the fixed effects of knowledge score, activity, and their interaction, and the random effects of participant and video (Figure 16). A significant main effect of knowledge was present (z = 8.81, p < .001) such that as knowledge increased, recognition performance also increased. No other effects were present (all p > .05).

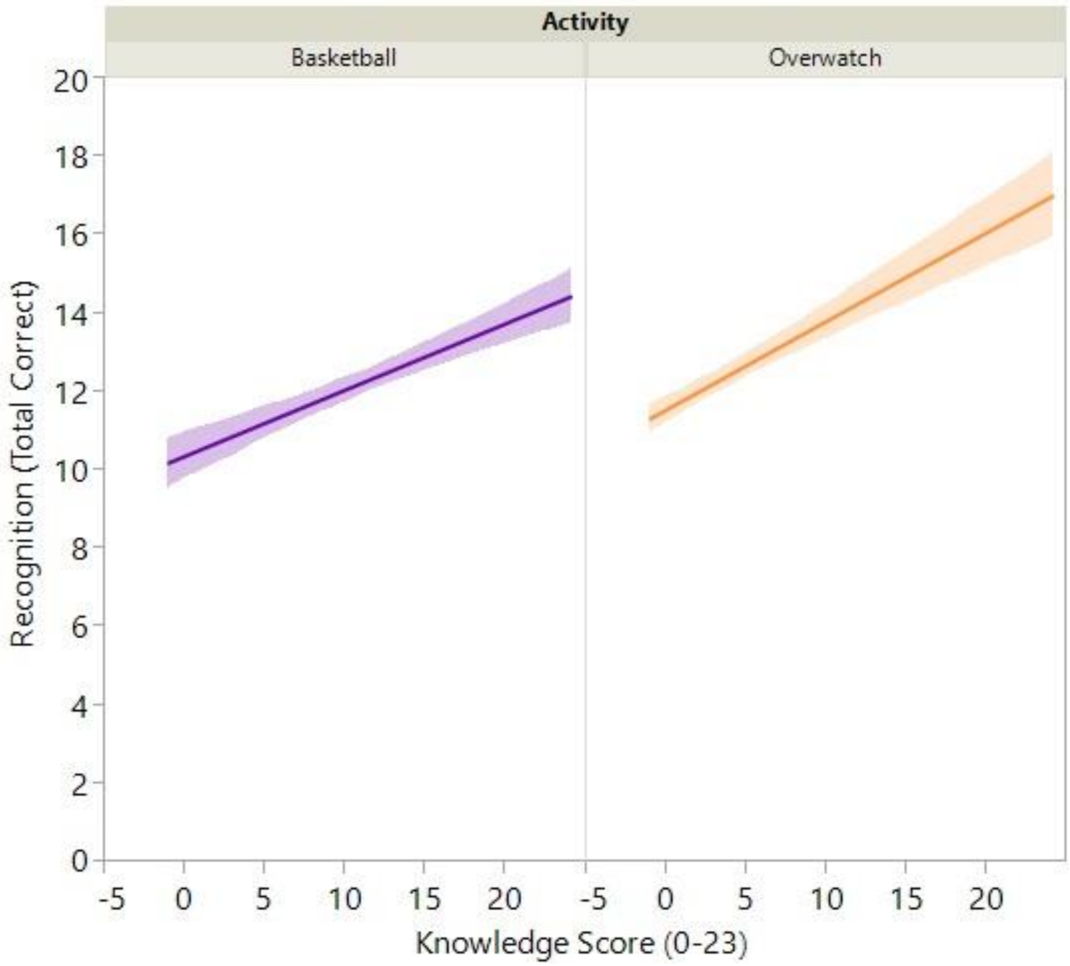


Figure 16. Exploratory Analysis: Knowledge predicting recognition performance

.

Segmentation and recognition.

Coarse segmentation. A generalized Poisson multilevel model was used to predict recognition performance from the full factorial of the fixed effects of coarse segmentation agreement, knowledge score, and activity and the random effects of participant and video (Figure 17). Aside from the main effect of knowledge reported above, no other effects were significant (all $p > .05$). This result does not replicate results from the main analyses such that effects of segmentation agreement on memory were not present here. One explanation could be the restricted range in the knowledge score for Overwatch.

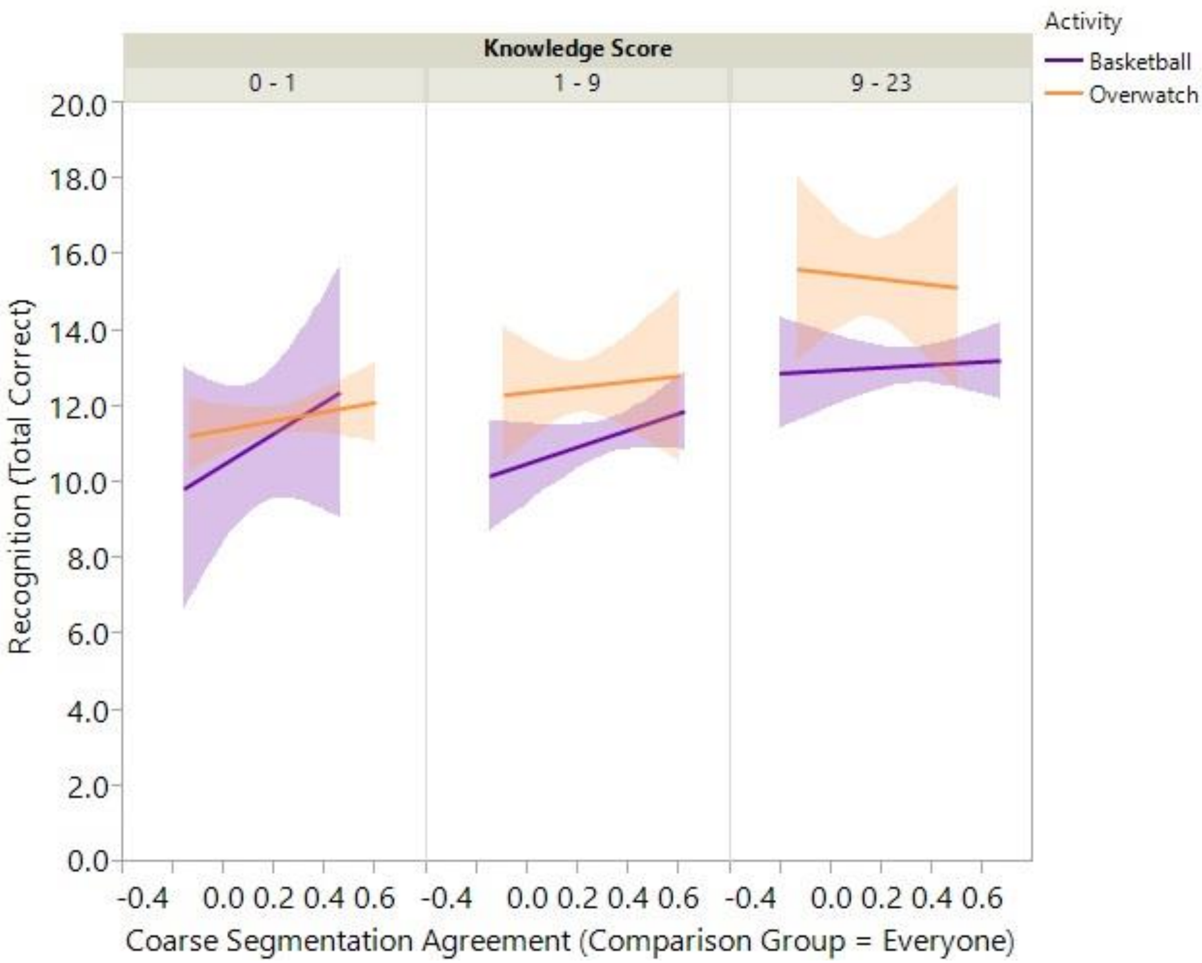


Figure 17. Exploratory Analysis: Coarse segmentation agreement and knowledge predicting recognition performance

Fine segmentation. A generalized Poisson multilevel model was used to predict recognition performance from the full factorial of the fixed effects of fine segmentation agreement, knowledge score, and activity and the random effect of participant (Figure 18). Video was not included in the random effects structure because the model was unable to converge. As with coarse segmentation agreement, only the main effect of knowledge score was present (z = 4.83, p < .001; all other effects, p > .05).

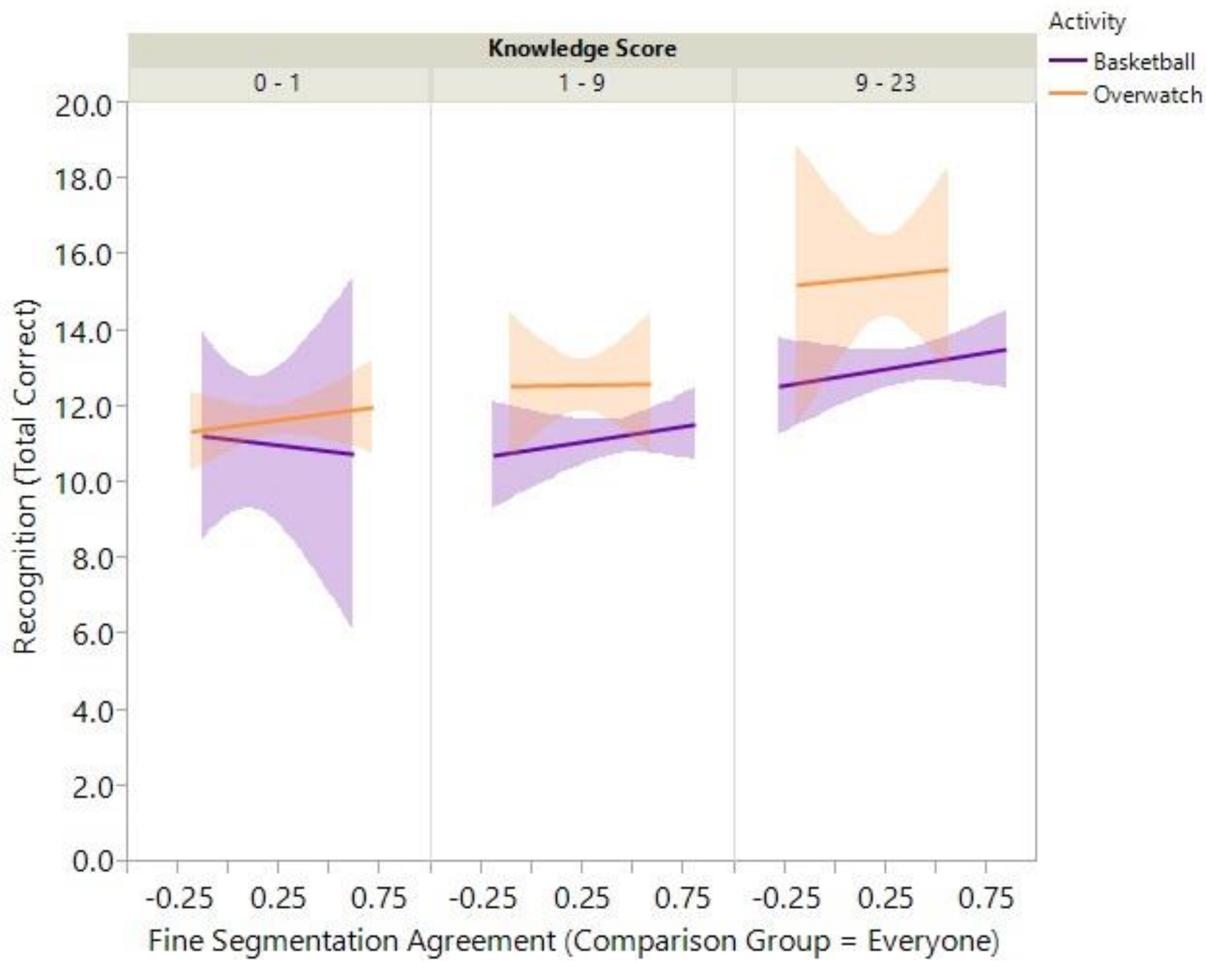


Figure 18. Exploratory Analysis: Fine segmentation agreement and knowledge predicting recognition performance

Hierarchical alignment and recognition. A generalized Poisson multilevel model was used to predict recognition performance from the full factorial of the fixed effects of temporal distance, knowledge score, and activity and the random effect of participant. Video was not included as a random effect because the model would not converge. As was found using segmentation agreement, only a significant main effect of knowledge score was present (z = 5.54, p < .001; Figure 19), suggesting that encoding organization as measured by temporal distance did not influence recognition, regardless of activity.

The same model was conducted using enclosure as the measure of alignment, rather than temporal distance. Again, only a significant main effect of knowledge was present ($z = 3.00$, $p = .003$; Figure 20). No other effects were significant (all $p > .05$). Altogether, these results replicated the lack of effects of hierarchical alignment on recognition, as was found in the results of the main analyses.

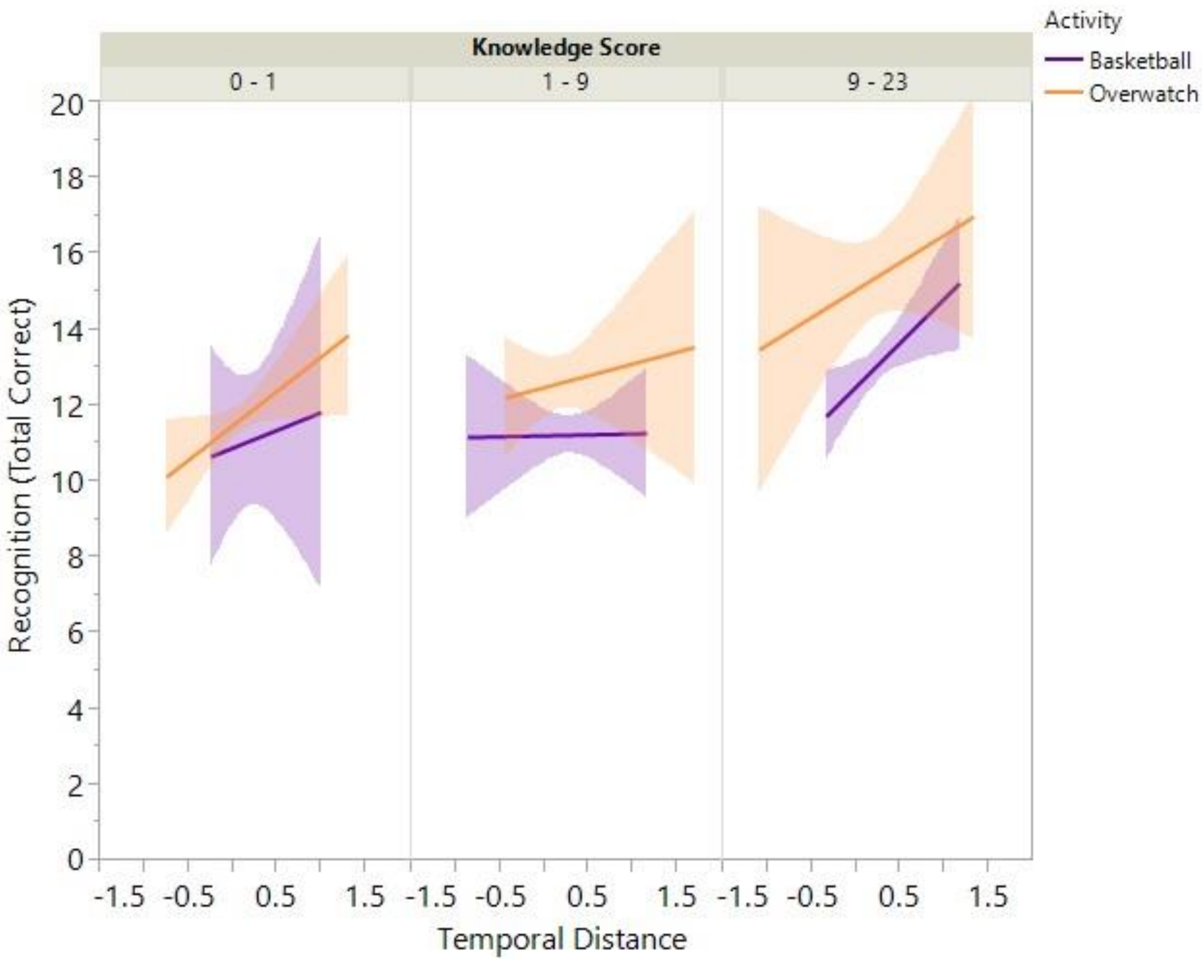


Figure 19. Exploratory Analysis: Temporal distance, knowledge, and activity predicting recognition performance

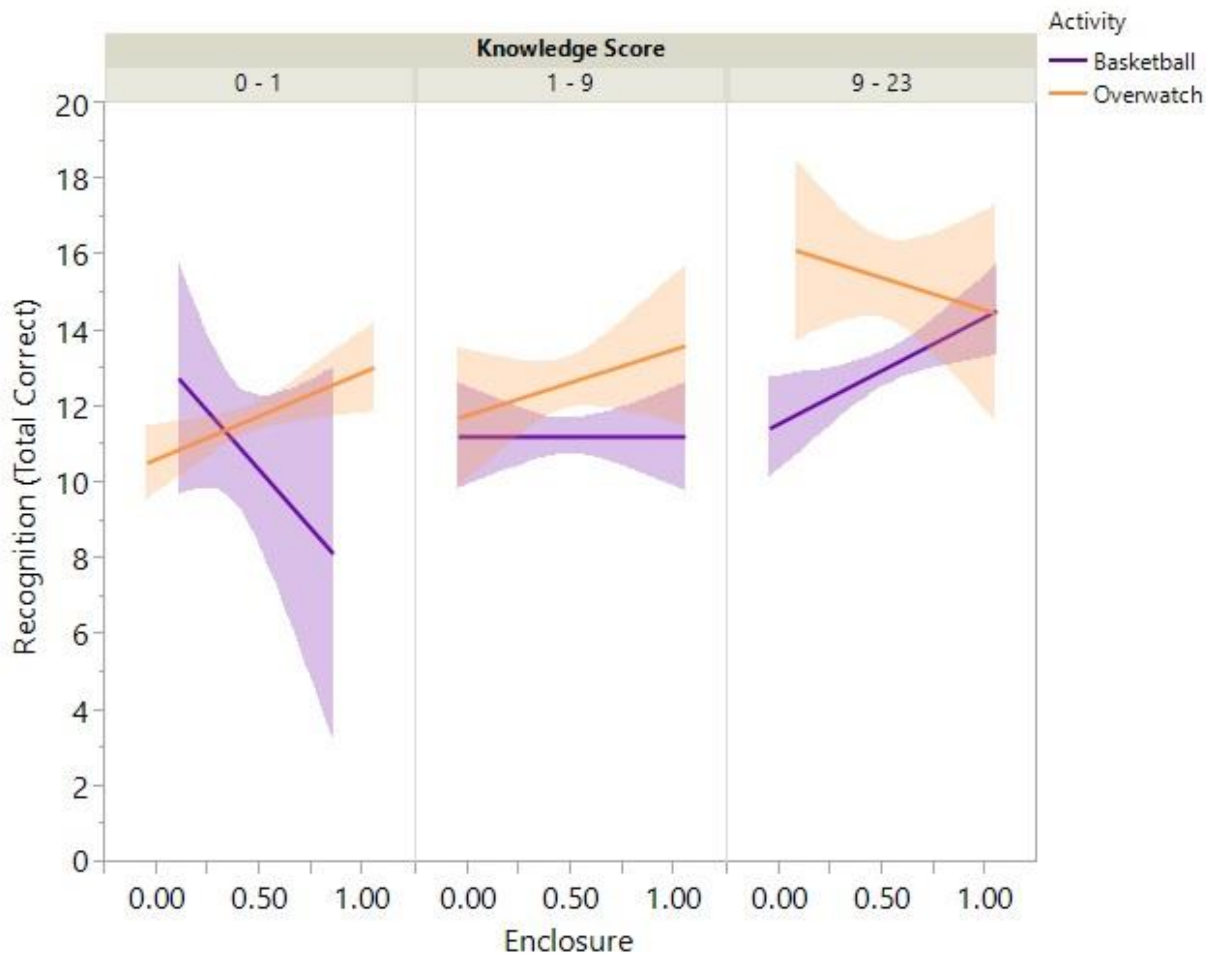


Figure 20. Exploratory Analysis: Enclosure, knowledge, and activity predicting recognition performance

.

Table 11. Summary of Main Analyses

Summary of Main Analyses

Measure	DV	IV(s)	*t* or *z*	Hypothesis Supported
Segmentation	Segmentation Frequency			
		Group	1.28	-
		Activity	1.77	-
		Grain	* -49.63	-
		Group x Activity	-1.10	-
		Group x Grain	* -11.11	-
		Activity x Grain	-.50	-
		Group x Activity x Grain	* -3.17	Differentiation
	Segmentation Agreement			
		Group	1.23	-
		Activity	1.78	-
		Grain	* -4.05	-
		Group x Activity	.18	-
		Group x Grain	1.16	-
		Activity x Grain	-1.44	-
		Group x Activity x Grain	* 2.29	Conceptual
Hierarchical Alignment	Temporal Distance			
		Group	.22	-
		Activity	* 3.99	Perceptual
		Group x Activity	-1.62	-
	Enclosure			
		Group	* 2.07	-
		Activity	3.27	-
		Group x Activity	* 2.03	Conceptual
Memory	Recognition			
		Group	* 3.52	-

	Activity	.89	-
	Group x Activity	* 5.05	Expertise
Temporal Order			
	Group	-.38	-
	Activity	* -2.08	-
	Group x Activity	-.15	-
Coarse Segmentation & Memory			
Recognition			
	Group	-.98	-
	Activity	* 2.51	-
	Coarse Segmentation Agreement	* 1.96	Segmentation Benefit
	Group x Activity	* -2.97	Expertise
	Group x Coarse Segmentation Agreement	-.79	-
	Activity x Coarse Segmentation Agreement	* -2.23	Segmentation Benefit
	Group x Activity x Coarse Segmentation Agreement	ƚ 1.90	Poor-get-richer
Fine Segmentation & Memory			
Recognition			
	Group	-1.13	-
	Activity	* 2.76	-
	Fine Segmentation Agreement	1.48	-
	Group x Activity	* -3.26	Expertise
	Group x Fine Segmentation Agreement	-.77	-
	Activity x Fine Segmentation Agreement	* -2.31	Segmentation Benefit
	Group x Activity x Fine Segmentation Agreement	ƚ 1.87	Poor-get-richer
Enclosure & Memory			
Recognition			

Group	.02	-
Activity	1.72	-
Enclosure	1.77	-
Group x Activity	-1.44	-
Group x Enclosure	-1.14	-
Activity x Enclosure	-1.02	-
Group x Activity x Enclosure	.43	Null

Note: * indicates significance of $p \leq .05$. ǂ indicates significance of $p = .06$. Hypotheses reported if predictions were made for those specific variables.

Table 12. Summary of Exploratory Analyses

Summary of Exploratory Analyses

Measure	DV	IV(s)	*t* or *z*	Hypothesis Supported
Segmentation				
	Segmentation Frequency			
		Knowledge	* -14.41	Conceptual
		Activity	* 5.70	-
		Grain	* 14.57	-
		Knowledge x Activity	* 7.55	Conceptual
		Knowledge x Grain	* 19.33	Conceptual
		Activity x Grain	* -10.15	-
		Knowledge x Activity x Grain	1.61	Perceptual
	Segmentation Agreement			
		Knowledge	-1.53	-
		Activity	1.87	-
		Grain	* -6.13	-
		Knowledge x Activity	* 2.53	Conceptual
		Knowledge x Grain	-.59	-
		Activity x Grain	-1.04	-
		Knowledge x Activity x Grain	* 3.22	Conceptual
Hierarchical Alignment				
	Temporal Distance			
		Knowledge	1.16	-
		Activity	* 3.24	Perceptual
		Knowledge x Activity	* -2.14	Conceptual
	Enclosure			
		Knowledge	* 2.52	Conceptual
		Activity	1.20	-

		Knowledge x Activity	* 2.33	Conceptual
Memory				
	Recognition			
		Knowledge	* 8.81	Expertise
		Activity	-1.66	-
		Knowledge x Activity	-.85	-
Coarse Segmentation & Memory				
	Recognition			
		Knowledge	* 5.22	Expertise
		Activity	-1.10	-
		Coarse Segmentation Agreement	1.68	-
		Knowledge x Activity	-.22	-
		Knowledge x Coarse Segmentation Agreement	-.85	-
		Activity x Coarse Segmentation Agreement	-.23	-
		Knowledge x Activity x Coarse Segmentation Agreement	-.18	Null
Fine Segmentation & Memory				
	Recognition			
		Knowledge	* 4.83	Expertise
		Activity	-1.67	-
		Fine Segmentation Agreement	.82	-
		Knowledge x Activity	-.54	-
		Knowledge x Fine Segmentation Agreement	-.63	-
		Activity x Fine Segmentation Agreement	.16	-
		Knowledge x Activity x Fine Segmentation Agreement	.18	Null
Enclosure & Memory				
	Recognition			
		Knowledge	* 3.00	Expertise

		Activity	.17	-
		Enclosure	.66	-
		Knowledge x Activity	-1.70	-
		Knowledge x Enclosure	-.17	-
		Activity x Enclosure	-1.20	-
		Knowledge x Activity x Enclosure	1.46	Null
Temporal Distance & Memory				
	Recognition			
		Knowledge	* 5.54	Expertise
		Activity	-1.51	-
		Temporal Distance	.60	-
		Knowledge x Activity	-1.36	-
		Knowledge x Temporal Distance	.51	-
		Activity x Temporal Distance	-.93	-
		Knowledge x Activity x Temporal Distance	1.26	Null

Note: * indicates significance of $p \leq .05$.

Discussion

Overall, the results of Experiment 2 replicated the effect of expertise on memory, specifically recognition, and suggested that experts segment information in their expert domain differently than information outside their domain. Specifically, experts segmented as often as novices at the coarse grain, regardless of activity; however, experts segmented more often than novices at the fine grain, particularly for events within their area of expertise. These results did not replicate previous findings that have suggested familiarity leads to the identification of fewer event boundaries (e.g., Blasing, 2015). Interestingly, experts showed better coarse segmentation agreement in their field of expertise despite the fact that they did not segment more often than novices. These results indicate that basketball experts share a similar understanding of the event and identify similar coarse event boundaries. It is also possible that experts' timing is more precise than novices' at identifying important changes in an event within one's field of expertise; however, this possibility cannot be evaluated in the current study. Importantly, experts' superior memory for information in their expert domain did not appear to result from better segmentation ability. Rather, segmentation seemed to aid experts' memory when they lacked knowledge for an activity. Interestingly, the effects of segmentation on memory disappeared when knowledge was treated as a continuous predictor in the exploratory analyses, rather than categorical in the main analyses. Altogether, there is initial evidence to suggest that knowledge and segmentation influence memory independently.

Chapter 5 - General Discussion

The current study aimed to replicate and extend the literature on expertise and event cognition by evaluating whether expertise influences segmentation and memory for events within and outside of one's area of expertise. In Experiment 1, an Overwatch knowledge survey was developed and validated so that we could identify experts and novices in Experiment 2. In Experiment 2, basketball experts and novices segmented videos of basketball and Overwatch, then had their memory assessed for the videos. Overall, experts' segmentation and memory ability for activities within their area of expertise differed from that of the novices (between-groups comparison) and also differed from their own segmentation and memory ability for activities outside their area of expertise (within-subjects comparison). Importantly, however, experts' superior memory was not a product of their more efficient segmentation ability, suggesting that effects of knowledge and segmentation may influence memory independently. Explanations for these findings are outlined below.

Differences at Encoding? Check!

Identifying Boundaries

Previous work evaluating the influence of expertise and familiarity on segmentation has found that fewer meaningful subevents are identified as individuals gain knowledge for, or familiarity with, an activity (e.g., Blasing, 2015; Hard et al., 2006; Levine et al., 2017). The current study did not replicate these findings. In fact, we found the opposite, depending on which grain of segmentation individuals were using. At the coarse level, basketball experts did not differ from novices on the number of perceived event boundaries. However, at the fine level, experts identified more event boundaries, particularly for the activity in which they had expert knowledge. Neither Blasing (2015) nor Levine et al. (2017) distinguished between coarse and fine boundary identification.

One explanation for the current finding comes from Hard et al., (2006). Specifically, they found that the identification of boundaries decreased when individuals were presumably "confused (overwhelmed)" (Hard et al., 2006; pg. 1228). It is possible that the lack of a difference in coarse boundary identification between experts and novices may have been due to novices' "confusion" regarding the activities, which may have led them to segment less often.

Another explanation comes from the literature on experts' perceptual processing abilities suggesting that experts are better at differentiating between information in their field of expertise (Herzmann & Curran, 2011). Evaluation of experts' superior differentiation abilities has been restricted to object categorization and feature processing, as opposed to perception of dynamic events. However, based on the evidence found in the current study, experts may be engaging in differentiation processing when identifying fine subevents for dynamic activities within their field of expertise. Future studies ought to further evaluate the influence of knowledge on coarse and fine segmentation to better understand how experts perceive event structure within their domain of expertise.

Agreeing on Boundaries

Levine et al., (2017) found that experts in figure skating agreed on the major subevents within the figure skating routine. The current study replicated this effect at the coarse grain level. Interestingly, this higher agreement among experts at the coarse grain was not due to their identifying more coarse-grain boundaries because they identified a similar number of coarse boundaries as the novices. Of the coarse boundaries identified by experts and novices, experts identified more similar boundaries, for basketball, whereas novices displayed more idiosyncratic coarse boundary identification (lower agreement). Experts seem to use their similar knowledge base to guide their segmentation. It is also possible that experts may be more precise in their timing when identifying boundaries, compared to novices who may be slower to notice important changes. Research from the motor perception literature suggests that motor expertise modulates action anticipation (basketball - Aglioti, Cesari, Romani, & Urgesi, 2008; music - Wollner & Canal-Bruland, 2010), such that observers are better at anticipating the actions of others when they themselves have experience performing the same action.

Interestingly, segmentation agreement of fine boundaries for experts and novices did not differ, despite experts identifying more fine boundaries for basketball. This finding suggests that identification of fine boundaries may be driven more by changes in perceptual cues, such as motion. Though previous work from the perceptual processing literature has shown that experts are better at engaging in differentiation for information in their expert domain (e.g., Herzmann & Curran, 2011), this explains why experts identified more fine boundaries, but does not necessarily explain the similarity between experts' and novices' fine segmentation agreement. Perceptual cues are available to both experts and novices during the entire time they are encoding the information. If experts and novices were both relying on the same perceptual cues to guide their segmentation, they could have identified more similar boundaries, which could increase the likelihood of similar agreement among identified boundaries; however, this does not explain why experts identified more boundaries in the first place.

Organization of Boundaries

Previous research has found no influence of knowledge on hierarchical alignment differences (Sargent et al., 2013). The current study found mixed results. Experts showed better enclosure of coarse and fine boundaries for basketball; however, all participants, regardless of knowledge, perceived basketball as more structured than Overwatch, when measured as temporal distance. Additionally, hierarchical alignment did not predict recognition performance. These findings seem to suggest that hierarchical alignment of coarse and fine events is minimally affected by knowledge and not as important to retrieval as segmentation agreement. Future research could include recall measures to assess whether effects of knowledge on hierarchical alignment are more evident depending on the way in which memory for activities is measured.

One explanation for the mixed results concerning hierarchical alignment could be the potential structural differences between basketball and Overwatch, which would have been more important if Overwatch experts were included in the analyses. Perhaps hierarchical alignment differences are more evident when the activity does not have an overarching goal or has more of a linear or sequential structure (Trabasso & Suh, 1993). For example, in text comprehension, causal relatedness between sentences can influence online comprehension of the text (Trabasso & Suh, 1993). Unfortunately, due to recruitment issues, Overwatch experts were few and far between; thus, their encoding organization could not be compared to novices' encoding organization for Overwatch specifically (and everyone included in the main analyses for the current study were novices in Overwatch). It is possible that experts in Overwatch would have been better able to organize coarse and fine events at encoding for Overwatch, compared to novices. Interestingly, however, Feller et al., (in prep) found that basketball experts perceived structure of basketball games better compared to novices, conceptually replicating the encoding organization effects found with basketball experts in the current study. Future research should continue to investigate effects of event structure on segmentation.

Altogether, experts and novices showed differences on a majority of the dependent measures of encoding, suggesting that experts encode dynamic information within their field of expertise differently than information outside their field of expertise. These findings support EST, such that expert knowledge was found to influence segmentation ability. It is important to note that the current findings may not have been present had grain size (coarse and fine) not been included. Including this manipulation allowed us to further investigate the levels of encoding or online event processing on which knowledge may have an effect, which is important for revising EST or translating these effects to applied scenarios, such as education.

Differences at Retrieval? Check!

The current study replicated decades of research demonstrating experts' superior memory for information within their field of expertise. Here, basketball experts exhibited more accurate recognition performance compared to novices, particularly for basketball videos, suggesting that knowledge facilitated memory. Unfortunately, due to poor internal consistency (Cronbach's alpha = .22), the order memory results were not interpretable. The task itself was quite difficult in that participants were presented with two images depicting events taken from the videos they watched. Participants were asked to choose which of those images depicted the action that occurred more recently. Relatedly, there were only 8 trials per video, which likely limited the amount of variability to discriminate group differences in order memory. It is possible that another measure of order memory would be more sensitive to group differences in memory for temporal order.

Does Encoding Predict Retrieval? It Depends.

A major goal of the current study was to evaluate whether experts' superior memory for events within their field of expertise was due to more efficient segmentation. Importantly, experts had more knowledge for basketball and this knowledge led to better segmentation ability. The between subjects effect of knowledge on segmentation for basketball at the coarse grain was moderate (d = .42) and the within-subjects effect was large (d = .96), thus showing comparable effect sizes to prior work showing moderate (e.g., d = .33, Newberry & Bailey, under review) and large (e.g., η^2 = .26, Levine et al., 2017) effects of knowledge and expertise on segmentation, respectively. Further, segmentation ability predicted recognition, which replicated previous work showing better segmentation agreement was related to better memory (e.g., Bailey et al., 2013; Flores et al., 2017; Sargent et al., 2013) and generally supports the fourth principle of EHM. Interestingly, however, this relationship was only present when experts *lacked* knowledge for the activity, suggesting that experts' superior memory in their domain of expertise was not due to better segmentation of the event information.

One explanation for this effect is that segmentation helps individuals understand what is going on in the moment, but when knowledge is present for an activity, semantic knowledge structures (e.g., schemas, scripts) may be more important in guiding memory for the activity. When knowledge for the event is lacking, presumably a schema for the information does not exist or is impoverished; therefore, a schema will not effectively guide memory. In this case, reliance on a more efficient encoding mechanism, such as segmentation (e.g., event models), might prove more useful in guiding memory. This would suggest that both segmentation and knowledge influence memory, but they do so independently of one another. Relatedly, segmentation is not the only encoding mechanism that might benefit memory. The basketball experts in the current study could have engaged in other encoding mechanisms or strategies (e.g., semantic chunking or elaboration) to guide their encoding and later retrieval of the basketball events. Future research should attempt to tease apart experts' and novices' reliance on schema and event structure when trying to remember information from events within and outside of one's expert area.

Alternatively, segmentation may benefit memory for event boundary (compared to non-boundary) information. According to EHM, segmentation guides memory because event boundaries serve as anchors that help differentiate between events (Radvansky & Zacks, 2017). The current study did not dissociate between event boundary and non-boundary information during the recognition task; therefore, we could not discern whether segmentation would predict memory for event boundary information or whether knowledge would influence that particular relationship. A future study could evaluate whether memory for event boundary information would benefit from efficient segmentation and whether this relationship would be influenced by knowledge.

An important note to mention is that the measure of memory in the current study was recognition[2]. Previous work investigating the relationship between segmentation and memory has used measures of recall (e.g., Flores et al., 2017; Sargent et al., 2013). It is possible that effects of knowledge on segmentation and memory may be more prominent through recall. Research suggests that recognition is easier than recall because it provides relevant cues to the individual and allows individuals to rely on retrieval and feelings of familiarity (Schwartz, 2018). Recall, on the other hand, does not use (or uses limited) cues, and requires that the individual retrieve the information rather than identify the information. The differences in memory in the current study may not have been large enough to see a benefit of knowledge on segmentation predicting memory due to the relative "easiness" of the task.

[2] Order memory was also assessed; however, the order memory task employed here was unreliable (alpha = .22).

Limitations

The current study was subject to a few limitations. First, the largest issue was participant recruitment. Recruitment of Overwatch experts was particularly difficult, even after targeting a group on campus comprised of individuals who play Overwatch regularly. Ultimately, this group of participants was dropped from the main analyses of the current study. Part of this difficulty may have been due to unfortunate timing with the release of a new, more popular video game, Fortnite (Ranker, 2018). Future work may have more success by recruiting experts online through sites such as MTurk.

Despite losing that group, it should be noted that the merit of the current work remains significant. Both between and within-subject comparisons were conducted, which sets this work apart from previous work (e.g., Blasing, 2015; Levine et al., 2017), and most importantly, the control novices did not show the same segmentation benefit as the experts for basketball, suggesting that the effects shown were due to differences in knowledge, not stimulus.

A second limitation was the unreliability of the order memory task. Performance on this task was at chance, suggesting that the instructions were not clear or that the task itself was too difficult. Ultimately, the results from this task were inconclusive. Due to this, the current study was only able to investigate the effect of knowledge and segmentation on one memory measure: a forced-choice recognition task. Moving forward, pilot studies testing different instructions or target images for the order memory task should be conducted before use in an experiment.

Finally, as previously stated, recall was not assessed in the current study. This choice was made due to the possibility of inherent vocabulary differences that could have put novices at a disadvantage when trying to describe the events of basketball and Overwatch. Future studies investigating this topic ought to consider including a measure of recall, as recall may be more sensitive to influences of knowledge (e.g., Anderson & Pichert, 1978; Bransford & Johnson, 1972).

Conclusions

Ultimately, support for EHM and EST were found, suggesting that knowledge aids memory and that knowledge influences segmentation ability. The current study found that expertise did improve event segmentation ability, but experts' superior memory for events within their field of expertise was not due to better segmentation ability. Evidence was present for both encoding and retrieval differences between experts and novices; however, preliminary evidence suggests that segmentation and knowledge appear to influence memory independently of one another.

References

Aglioti, S. M., Cesari, P., Romani, M., & Urgesi, C. (2008). Action anticipation and motor resonance in elite basketball players. *Nature Neuroscience*, *11*(9), 1109.

Allard, F., & Starkes, J. L. (1991). Motor-skill experts in sports, dance, and other domains. *Toward a general theory of expertise: prospects and limits*, 126-152.

Anderson, R. C., & Pichert, J. W. (1978). Recall of previously unrecallable information following a shift in perspective. *Journal of Verbal Learning and Verbal Behavior*, *17*(1), 1-12.

Bailey, H. (2012). Computer-paced versus experimenter-paced working memory span tasks: Are they equally reliable and valid? *Learning and Individual Differences*, *22*(6), 875-881.

Bailey, H. R., Zacks, J. M., Hambrick, D. Z., Zacks, R. T., Head, D., Kurby, C. A., & Sargent, J. Q. (2013). Medial temporal lobe volume predicts elders' everyday memory. *Psychological Science*, *24*(7), 1113-1122.

Baldwin, D. A., Baird, J. A., Saylor, M. M., & Clark, M. A. (2001). Infants parse dynamic action. *Child Development*, *72*(3), 708-717.

Bartlett, F. C. (1932). Remembering: An experimental and social study. *Cambridge: Cambridge University*.

Bauer-Wolf, J. (June 2017). *Video games as a college sport*. Retrieved from https://www.insidehighered.com/news/2017/06/09/esports-quickly-expanding-colleges

Bläsing, B. E. (2015). Segmentation of dance movement: effects of expertise, visual familiarity, motor experience and music. *Psychological Perspectives on Expertise*, 64.

Blizzard Entertainment ©. (n.d.). Retrieved January, 2018 from Blizzard Entertainment: https://playoverwatch.com/en-us/

Bower, G. H., Black, J. B., & Turner, T. J. (1979). Scripts in memory for text. *Cognitive Psychology*, *11*(2), 177-220.

Bransford, J. D., & Johnson, M. K. (1972). Contextual prerequisites for understanding: Some investigations of comprehension and recall. *Journal of Verbal Learning and Verbal Behavior*, *11*(6), 717-726.

Bukach, C. M., Gauthier, I., & Tarr, M. J. (2006). Beyond faces and modularity: the power of an expertise framework. *Trends in Cognitive Sciences*, *10*(4), 159-166.

Chase, W. G., & Simon, H. A. (1973). Perception in chess. *Cognitive Psychology*, *4*(1), 55-81.

Chiesi, H. L., Spilich, G. J., & Voss, J. F. (1979). Acquisition of domain-related information in relation to high and low domain knowledge. *Journal of Verbal Learning and Verbal Behavior*, *18*(3), 257-273.

de Groot, A. D. (1966). Perception and Memory Versus Thought: Some Old Ideas and Recent Findings. In B. Kleinmuntz (Ed.), *Problem Solving, Research, Method and Theory*. New York: Krieger, 1966.

DuBrow, S., & Davachi, L. (2014). Temporal memory is shaped by encoding stability and intervening item reactivation. *Journal of Neuroscience*, *34*(42), 13998-14005.

Engle, R. W., & Bukstel, L. (1978). Memory processes among bridge players of differing expertise. *The American Journal of Psychology*, 673-689.

Ericsson, K. A., & Smith, J. (Eds.). (1991). *Toward a general theory of expertise: Prospects and limits*. Cambridge University Press.

Ericsson, K. A., Delaney, P. F., Weaver, G. A. & Mahadevan, S. (2004). Uncovering the structure of a memorist's superior "basic" memory capacity. *Cognitive Psychology, 49,* 191–237.

Feller, D. F., Schwan, S., Wiemer, K., & Magliano, J. P. (in prep). Event Segmentation and Expertise.

French, K. E., & Thomas, J. R. (1987). The Relation of Knowledge Development to Children's Basketball Performance. *Journal of Sport Psychology*, *9*(1), 15-32.

Flores, S., Bailey, H. R., Eisenberg, M. L., & Zacks, J. M. (2017). Event segmentation improves event memory up to one month later. *Journal of Experimental Psychology: Learning, Memory & Cognition, 43,* 1183-1202.

Gilhooly, K. J., Wood, M., Kinnear, P. R., & Green, C. (1988). Skill in map reading and memory for maps. *The Quarterly Journal of Experimental Psychology*, *40*(1), 87-107.

Gobet, F., & Chassy, P. (2009). Expertise and intuition: A tale of three theories. *Minds and Machines*, *19*(2), 151-180.

Gobet, F., & Simon, H. A. (1996). Recall of random and distorted chess positions: Implications for the theory of expertise. *Memory & Cognition*, *24*(4), 493-503.

Gobet, F., & Simon, H. A. (1996). Recall of rapidly presented random chess positions is a function of skill. *Psychonomic Bulletin & Review*, *3*(2), 159-163.

Gobet, F., & Simon, H. A. (1996). Templates in chess memory: A mechanism for recalling several boards. *Cognitive Psychology*, *31*(1), 1-40.

Gobet, F., & Simon, H. A. (1996). The roles of recognition processes and look-ahead search in time-constrained expert problem solving: Evidence from grand-master-level chess. *Psychological Science*, *7*(1), 52-55.

Goldin, S. E. (1979). Recognition memory for chess positions: Some preliminary research. *The American Journal of Psychology*, *92*, 19–31.

Goldstone, R. L. (1998). Perceptual learning. *Annual Review of Psychology*, *49*(1), 585-612.

Hambrick, D. Z., & Engle, R. W. (2002). Effects of domain knowledge, working memory capacity, and age on cognitive performance: An investigation of the knowledge-is-power hypothesis. *Cognitive Psychology*, *44*(4), 339-387.

Hard, B. M., Lozano, S. C., & Tversky, B. (2006). Hierarchical encoding of behavior: Translating perception into action. *Journal of Experimental Psychology: General*, *135*(4), 588.

Hard, B. M., Recchia, G., & Tversky, B. (2011). The shape of action. *Journal of Experimental Psychology, 140*, 586-604. doi:10.1037/a0024310

Hard, B. M., Tversky, B., & Lang, D. S. (2006). Making sense of abstract events: Building event schemas. *Memory & Cognition*, *34*(6), 1221-1235.

Herzmann, G., & Curran, T. (2011). Experts' memory: an ERP study of perceptual expertise effects on encoding and recognition. *Memory & Cognition*, *39*(3), 412-432.

Kane, M. J., Hambrick, D. Z., Tuholski, S. W., Wilhelm, O., Payne, T. W., & Engle, R. W. (2004). The generality of working memory capacity: a latent-variable approach to verbal and visuospatial memory span and reasoning. *Journal of Experimental Psychology: General*, *133*(2), 189.

Kurby, C. A., & Zacks, J. M. (2008). Segmentation in the perception and memory of events. *Trends in Cognitive Sciences*, *12*(2), 72-79.

Kurby, C. A., & Zacks, J. M. (2011). Age differences in the perception of hierarchical structure in events. *Memory & Cognition*, *39*(1), 75-91.

Levine, D., Hirsh-Pasek, K., Pace, A., & Michnick Golinkoff, R. (2017). A goal bias in action: The boundaries adults perceive in events align with sites of actor intent. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *43*(6), 916.

Loschky, L. C., Larson, A. M., Magliano, J. P., & Smith, T. J. (2015). What would Jaws do? The tyranny of film and the relationship between gaze and higher-level narrative film comprehension. *PloS one*, *10*(11), e0142474.

Magliano, J. P., Miller, J., & Zwaan, R. A. (2001). Indexing space and time in film understanding. *Applied Cognitive Psychology*, *15*(5), 533-545.

Mann, D. T. Y., Williams, A. M., Ward, P., & Janelle, C. M. (2007). Perceptual-cognitive expertise in sport: A meta-analysis. *Journal of Sport and Exercise Psychology, 29*, 457–478.

Mcpherson, S. L. (1993). Knowledge representation and decision-making in sport. *Advances in Psychology*, *102*, 159-188.

Meinz, E. J., & Salthouse, T. A. (1998). The effects of age and experience on memory for visually presented music. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *53*(1), P60-P69.

Newberry, K., Smith, M., & Bailey, H. (in prep). Age-related changes in the effects of knowledge on event segmentation and memory.

Newberry, K., & Bailey, H. (under review). Does semantic knowledge influence event segmentation and recall. *Memory and Cognition.*

Newtson, D. (1973). Attribution and the unit of perception of ongoing behavior. *Journal of Personality and Social Psychology*, *28*(1), 28.

Newtson, D., Engquist, D., & Bois, J. (1977). The objective basis of behavior unit. *Journal of Personality and Social Psychology*, *35*(12), 847-862.

Overwatch. (2005-2018). Retrieved January, 2018 from the Overwatch Wiki: https://overwatch.gamepedia.com/Overwatch_Wiki

Piras, A., Lobietti, R., & Squatrito, S. (2010). A study of saccadic eye movement dynamics in volleyball: comparison between athletes and non-athletes. *Journal of Sports Medicine and Physical Fitness*, *50*(1), 99.

Radvansky, G. A. (2012). Across the event horizon. *Current Directions in Psychological Science*, *21*(4), 269-272.

Radvansky, G. A., & Zacks, J. M. (2014). *Event Cognition*. Oxford University Press.

Radvansky, G. A., & Zacks, J. M. (2017). Event boundaries in memory and cognition. *Current Opinion in Behavioral Sciences*, *17*, 133-140.

Ranker Games. (n.d.). Retrieved November, 2018 from Ranker: https://www.ranker.com/list/most-popular-video-games-today/ranker-games

Rawson, K. A., & Van Overschelde, J. P. (2008). How does knowledge promote memory? The distinctiveness theory of skilled memory. *Journal of Memory and Language*, *58*(3), 646-668.

Recht, D. R., & Leslie, L. (1988). Effect of prior knowledge on good and poor readers' memory of text. *Journal of Educational Psychology*, *80*(1), 16.

Rosen, V. M., Caplan, L., Sheesley, L., Rodriguez, R., & Grafman, J. (2003). An examination of daily activities and their scripts across the adult lifespan. *Behavior Research Methods, Instruments, & Computers*, *35*, 32-48. doi:10.3758/BF03195495

Salthouse, T. A. (1993). Speed mediation of adult age differences in cognition. *Developmental Psychology*, *29*(4), 722.

Salthouse, T. A., & Babcock, R. L. (1991). Decomposing adult age differences in working memory. *Developmental Psychology*, *27*(5), 763.Sargent, J. Q., Zacks, J. M., Hambrick,

D. Z., Zacks, R. T., Kurby, C. A., Bailey, H. R., ... & Beck, T. M. (2013). Event segmentation ability uniquely predicts event memory. *Cognition*, *129*(2), 241-255.

Schank, R. C., & Abelson, R. P. (1977). Scripts, plans, goals, and understanding: An inquiry into human knowledge structures. Lawrence Erlbaum Associates, Inc.

Schwartz, B. L. (2018). *Memory: Foundations and applications*. SAGE Publications.

Smith, M., Newberry, K., & Bailey, H. (in prep). Differential effects of knowledge on encoding and memory for everyday activities in younger and older adults.

Snodgrass, J. G., & Vanderwart, M. (1980). A standardized set of 260 pictures: norms for name agreement, image agreement, familiarity, and visual complexity. *Journal of Experimental Psychology: Human Learning and Memory*, *6*(2), 174.

Speer, N. K., Swallow, K. M., & Zacks, J. M. (2003). Activation of human motion processing areas during event perception. *Cognitive, Affective, & Behavioral Neuroscience*, *3*(4), 335-345.

Spilich, G. J., Vesonder, G. T., Chiesi, H. L., & Voss, J. F. (1979). Text processing of domain-related information for individuals with high and low domain knowledge. *Journal of Verbal Learning and Verbal Behavior*, *18*(3), 275-290.

Tanaka, J. W., & Curran, T. (2001). A neural basis for expert object recognition. *Psychological Science*, *12*(1), 43-47.

Thompson, C. P., Cowan, T. M. & Frieman, J. (1993). *Memory Search by a Memorist.* Hillsdale, NJ: Lawrence Erlbaum Associates.

Trabasso, T., & Suh, S. (1993). Understanding text: Achieving explanatory coherence through on-line inferences and mental operations in working memory. *Discourse Processes*, *16*(1-2), 3-34.

Tversky, B., Zacks, J. M., & Martin, B. (2008). The structure of experience. In T. F. Shipley & J. M. Zacks (Eds.), *Understanding events: From perception to action*. (pp. 436-464).

Voss, J. F., Greene, T. R., Post, T. A., & Penner, B. C. (1983). Problem-solving skill in the social sciences. *Psychology of Learning and Motivation*, *17*, 165-213.

Walker, C. H. (1987). Relative importance of domain knowledge and overall aptitude on acquisition of domain-related information. *Cognition and Instruction*, *4*(1), 25-42.

Wetzels, R., & Wagenmakers, E. (2012). A default Bayesian hypothesis test for correlations and partial correlations. *Psychonomic Bulletin & Review, 19*(6), 1057-1064.

Wilder, D. A. (1978). Predictability of behaviors, goals, and unit of perception. *Personality and Social Psychology Bulletin*, *4*(4), 604-607.

Wöllner, C., & Cañal-Bruland, R. (2010). Keeping an eye on the violinist: motor experts show superior timing consistency in a visual perception task. *Psychological Research*, *74*(6), 579-585.

Zacks, J. M. (2004). Using movement and intentions to understand simple events. *Cognitive Science*, *28*(6), 979-1008.

Zacks, J. M., & Swallow, K. M. (2007). Event segmentation. *Current Directions in Psychological Science*, *16*, 80-84.

Zacks, J. M., & Tversky, B. (2003). Structuring information interfaces for procedural learning. J*ournal of Experimental Psychology: Applied, 9*, 88-100.

Zacks, J. M., Braver, T.S., Sheridan, M.A., Donaldson, D.I., Snyder, A.Z., Ollinger, J.M., Buckner, R.L., & Raichle, M.E. (2001). Human brain activity time-locked to perceptual event boundaries. *Nature Neuroscience, 4*, 651-655.

Zacks, J. M., Speer, N. K., & Reynolds, J. R. (2009). Segmentation in reading and film comprehension. *Journal of Experimental Psychology: General*, *138*(2), 307.

Zacks, J. M., Speer, N. K., Swallow, K. M., Braver, T. S., & Reynolds, J. R. (2007). Event perception: a mind-brain perspective. *Psychological Bulletin*, *133*(2), 273.

Zacks, J. M., Speer, N. K., Vettel, J. M., & Jacoby, L. L. (2006). Event understanding and memory in healthy aging and dementia of the Alzheimer type. *Psychology and Aging*, *21*(3), 466.

Zacks, J. M., Tversky, B., & Iyer, G. (2001). Perceiving, remembering, and communicating structure in events. *Journal of Experimental Psychology: General*, *130*(1), 29.

Appendix A - Stimuli Examples

Overwatch Survey

The following questions assess your knowledge about the video game Overwatch. For each question, mark your answer by clicking on the appropriate response. If you do not know the answer to a question, you may choose "I don't know." Please do not use outside sources to answer the questions.

1. What type of game is Overwatch?
    a. Team-based multiplayer online first-person shooter
    b. Massive multiplayer online roleplay
    c. Team-based multiplayer online roleplay
    d. Massive multiplayer online first-person shooter
    e. I don't know
2. Which company developed Overwatch?
    a. Valve
    b. Twitch
    c. Cloud Imperium
    d. Blizzard Entertainment
    e. I don't know
3. What are the characters in the game called?
    a. Heroes
    b. Villains
    c. Sims
    d. Avatars
    e. I don't know
4. Which of the following is not a character role in Overwatch?
    a. Offense
    b. Midfield
    c. Defense
    d. Support
    e. I don't know
5. How many players are on a team?
    a. 6
    b. 5
    c. 3
    d. 7
    e. I don't know
6. How many teams play during a game?
    a. 4
    b. 3
    c. 2
    d. 5
    e. I don't know

7. Which character role has high speed and attack but low defense?
    a. Offense
    b. Defense
    c. Support
    d. Tank
    e. I don’t know
8. Which character role forms choke points for enemies?
    a. Offense
    b. Support
    c. Defense
    d. Tank
    e. I don’t know
9. Which of the following is a way that players can switch characters during a match?
    a. Anytime they want to switch they can
    b. Reaching their opponents base
    c. Returning to their home base
    d. They can’t switch characters during a match
    e. I don’t know
10. Which of the following is not a method of earning in-round fire points?
    a. Killing or assisting in killing
    b. Providing team defense or healing
    c. Scoring objective points
    d. Leading a team
    e. I don’t know
11. Which of the following is not a type of map?
    a. Assault
    b. Escort
    c. Competitive
    d. Hybrid
    e. I don’t know
12. Which of the following is the name of the map that is based on London?
    a. King’s Row
    b. King’s Cross
    c. King’s Station
    d. King’s Throne
    e. I don’t know
13. Which of the following is the name of the map that is based on Egypt?
    a. Pyramids of Giza
    b. Temple of Anubis
    c. Temple of Osiris
    d. Pyramids of Khufu
    e. I don’t know

14. Which of the following is not an offense hero?
    a. Hanzo
    b. Doomfist
    c. Genji
    d. McCree
    e. I don’t know
15. Which of the following is not a defense hero?
    a. Bastion
    b. Junkrat
    c. Orisa
    d. Hanzo
    e. I don’t know
16. Which of the following is a support hero?
    a. Mercy
    b. Reinhardt
    c. D.Va
    d. Bastion
    e. I don’t know
17. Which of the following is a tank hero?
    a. Junkrat
    b. D.Va
    c. Lucio
    d. Ana
    e. I don’t know
18. Which of the following ultimates allows you to fly?
    a. Coalescence
    b. Blizzard
    c. Tactical Visor
    d. Valkyrie
    e. I don’t know
19. Which of the following ultimates allows Zenyatta to restore health?
    a. Transcendence
    b. Coalescence
    c. Super charger
    d. Shield generator
    e. I don’t know
20. Which of the following is not a method of filling the Ultimate Meter?
    a. Dealing damage to enemy heroes
    b. Healing
    c. Damage boosting
    d. Completing an objective
    e. I don’t know

21. In which game mode is the only objective to move the payload to a delivery point, while the defense halts the attacker's progress?
    a. Assault
    b. Escort
    c. Hybrid
    d. Control
    e. I don't know
22. Which of the following offense heroes relies more on team coordination?
    a. McCree
    b. Reaper
    c. Pharah
    d. Sombra
    e. I don't know
23. Which of the following support heroes is most useful when used as a defensive hero with supportive ultimates?
    a. Ana
    b. Mercy
    c. Symmetra
    d. Moira
    e. I don't know
24. I have a high level of Overwatch knowledge.
    a. Strongly disagree
    b. Somewhat disagree
    c. Neither agree nor disagree
    d. Somewhat agree
    e. Strongly agree
25. Please choose the option that best describes your involvement with Overwatch.
    a. I currently play Overwatch.
    b. I used to play often, but not anymore.
    c. I used to play a little, but not anymore.
    d. I have seen people play Overwatch, but I have never played.
    e. I have never seen people play Overwatch and I have never played.
26. How often do you play Overwatch?
    a. Daily
    b. Weekly
    c. Monthly
    d. Yearly
    e. Never
27. If you do play, please select the approximate number of hours per week that you spend playing Overwatch. If you do not play, please choose 0.
    a. 0
    b. 1-5
    c. 6-10
    d. 11-15
    e. 16 or more

28. Please enter the SR (rank) for your main account in the text field below. If you do not play, please enter 0.
29. I consider myself an Overwatch expert
    a. Strongly disagree
    b. Somewhat disagree
    c. Neither agree nor disagree
    d. Somewhat agree
    e. Strongly agree

Basketball Survey

The following questions assess your knowledge about Basketball. For each question, mark your answer by clicking on the appropriate response. If you do not know the answer to a question, you may choose “I don’t know.” Please do not use outside sources to answer the questions.

1. Which of the following is not the name of a basketball violation?
    a. Traveling
    b. Lane Violation
    c. Technical Foul
    d. Pass Interference
    e. I don’t know
2. Not inbounding the ball quickly enough results in a:
    a. 3-second violation
    b. 4-second violation
    c. 5-second violation
    d. 10-second violation
    e. I don’t know
3. If two opposing players are holding the ball simultaneously, the referee will call:
    a. A toss-up
    b. A jump-ball
    c. A scrum
    d. A dead-ball
    e. I don’t know
4. One and one is:
    a. A term for a one point shot
    b. A term for a team’s last warning
    c. A term for a free-throw penalty situation
    d. A term for a play design to free up a player
    e. I don’t know
5. What is the maximum amount of time an offensive player can be in the paint?
    a. 3 seconds
    b. 5 seconds
    c. 10 seconds
    d. 24 seconds
    e. I don’t know

6. How many fouls can an NBA player get before they foul out?
    a. 4
    b. 5
    c. 6
    d. 7
    e. I don’t know
7. Taking more than one step without dribbling is called:
    a. Scooting
    b. Sliding
    c. Double-dribbling
    d. Traveling
    e. I don’t know
8. How long is the shot clock in the NBA?
    a. 12 seconds
    b. 20 seconds
    c. 24 seconds
    d. 35 seconds
    e. I don’t know
9. In basketball, “goal-tending” is best defined as”
    a. Standing too close to the rim for too long
    b. Interfering with a shot on its downward trajectory
    c. Impeding the goal of an opposing player at an illegal time
    d. Rebounding the ball after a miss by the opposing team
    e. I don’t know
10. In basketball, what does “in-the-paint” mean?
    a. The area inside the free-throw lane
    b. The area outside the 3-point line
    c. The circular area near center court
    d. The location where players wait to enter the game
    e. I don’t know
11. Which of the following is not a position in basketball?
    a. A stretch 4
    b. Point-guard
    c. Tight-end
    d. Power-forward
    e. I don’t know
12. When can the inbounds passer run along the baseline to help get the ball inbound?
    a. Only after the opposing team scores
    b. Only in the 4^{th} quarter
    c. Only when being defended
    d. Anytime
    e. I don’t know
13. When can the rebounders enter the lane on a free-throw?
    a. As soon as the ball leaves the shooter’s hand
    b. When the ball is halfway to the basket
    c. As soon as the ball hits the rim

d. As soon as the ref blows the whistle
e. I don’t know

14. True or False: Each personal foul also counts as a team foul.
    a. True
    b. False
    c. I don’t know
15. How far from the basket is the free-throw line?
    a. 10 feet
    b. 15 feet
    c. 20 feet
    d. 25 feet
    e. I don’t know
16. When is a team allowed to make a substitution?
    a. Only during a dead-ball
    b. At any point throughout the game
    c. Only during a time-out
    d. Only after a basket is made
    e. I don’t know
17. Which positioned players typically have the lowest free-throw percentage?
    a. Point-guards
    b. Forwards
    c. Shooting-guards
    d. Centers
    e. I don’t know
18. What is an “alley-oop”?
    a. A bounce pass to a teammate
    b. When a player from the opposing team steals the ball
    c. A pass to a teammate who catches the ball in the air for a dunk
    d. A shot that goes off the back-board and into the hoop
    e. I don’t know
19. How long is a quarter in the NBA?
    a. 10 minutes
    b. 12 minutes
    c. 15 minutes
    d. 25 minutes
    e. I don’t know
20. When a player is in a triple threat position, he/she can do all of the following except:
    a. Shoot
    b. Dribble
    c. Pass
    d. Set a screen
    e. I don’t know

21. Which of the following is not a type of defense commonly used in basketball?
    a. Man to man
    b. Full coverage
    c. Zone
    d. Box and one
    e. I don't know
22. On defense, if you are screened by an offensive player, you should:
    a. Go in front of the player screening you
    b. Switch offensive players with a teammate
    c. Run toward the goal to rebound
    d. Either A or B are correct
    e. I don't know
23. When a player sets a screen or pick, he/she should:
    a. Roll to the basket with the front part of the body facing the teammate with the ball
    b. Roll to the basket with the back to the teammate with the ball
    c. Make sure to stick a knee out to block the defensive player
    d. None of the above
    e. I don't know
24. I have a high level of basketball knowledge.
    a. Strongly disagree
    b. Somewhat disagree
    c. Neither agree nor disagree
    d. Somewhat agree
    e. Strongly agree
25. Please choose the option that best describes your involvement with basketball.
    a. I currently play basketball.
    b. I used to play often, but not anymore.
    c. I used to play a little, but not anymore.
    d. I have seen people play basketball, but I have never played.
    e. I have never seen people play basketball and I have never played.
26. How often do you play basketball?
    a. Daily
    b. Weekly
    c. Monthly
    d. Yearly
    e. Never
27. If you do play, please select the approximate number of hours per week that you spend playing basketball. If you do not play, please choose 0.
    a. 0
    b. 1-5
    c. 6-10
    d. 11-15
    e. 16 or more

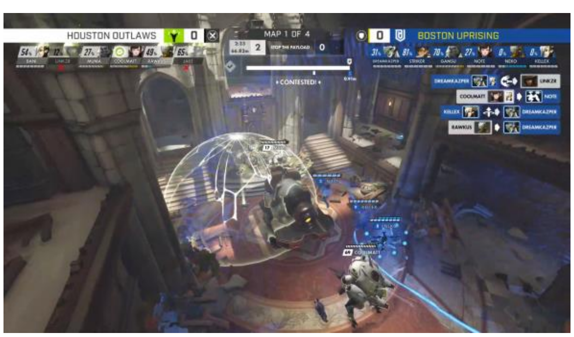
28. Please choose the highest level of basketball you have ever played.
    a. Never played
    b. Pick-up games
    c. Rec leagues
    d. High School
    e. College or Professional
29. I consider myself a basketball expert.
    a. Strongly disagree
    b. Somewhat disagree
    c. Neither agree nor disagree
    d. Somewhat agree
    e. Strongly agree
30. How often do you watch basketball during the season?
    a. Everyday
    b. At least once a week
    c. Once a month
    d. Once a year
    e. Never

Recognition Task: Example Trial

"Please choose the image that came from the video you just watched."

Order Memory Task: Example Trial

"Which of these images depicts the more recent action?"



Appendix B - Task Performance for All Expertise Groups

Table 13. Knowledge Scores by All Groups

Knowledge Scores by Expertise Group

	Basketball Experts	Overwatch Experts (Basketball Novices)	Overwatch Experts (Any Basketball Score)	Overwatch Experts (Combined)	Controls (Novices)	Intermediates
Overwatch	1.29 (.38)	19.67 (.67)	20.78 (.52)	20.50 (.44)	1.34 (.28)	3.15 (.64)
Basketball	20.06 (.27)	4.00 (.58)	16.56 (1.50)	13.42 (1.98)	4.51 (.29)	11.89 (.45)

Note: Standard error in parentheses. *Novice ≤ 7; Expert ≥ 17.*

Table 14. Cognitive Battery by All Groups

Cognitive Battery by Expertise Groups

	Basketball Experts	Overwatch Experts (Basketball Novices)	Overwatch Experts (Any Basketball Score)	Overwatch Experts (Combined)	Controls (Novices)	Intermediates
Letter Comparison	16.38 (.38)	16.33 (1.76)	17.44 (1.08)	17.17 (.89)	16.08 (.34)	16.74 (.38)
Pattern Comparison	21.17 (.63)	24.33 (1.20)	21.56 (1.64)	22.25 (1.29)	20.28 (.60)	20.56 (.62)
Semantic Knowledge	56.12 (1.45)	67.00 (2.65)	55.11 (4.88)	58.08 (3.97)	53.44 (1.47)	54.96 (1.56)
Vocabulary	14.03 (.48)	17.67 (1.20)	16.78 (1.62)	17.00 (1.23)	13.48 (.49)	13.74 (.43)
R-SPAN	0.8 (.02)	0.98 (.02)	0.83 (.06)	0.86 (.05)	0.77 (.02)	0.74 (.02)

Note: Standard error in parentheses.

Table 15. Segmentation Abilities by All Groups

Segmentation Abilities by Expertise Group

	Activity	Video	Grain	Segmentation Count	Segmentation Agreement (Own)	Segmentation Agreement (Expert)	Segmentation Agreement (Everyone)
Basketball Experts							
	Overwatch	HOUvBOS	Coarse	16.81 (2.27)	.24 (.02)	.20 (.02)	.28 (.02)
			Fine	41.64 (6.41)	.29 (.02)	.28 (.03)	.34 (.03)
		LONvFLA	Coarse	18.36 (2.61)	.14 (.02)	.09 (.02)	.16 (.02)
			Fine	42.36 (5.75)	.14 (.02)	.10 (.02)	.19 (.02)
	Basketball	MEMvUCLA	Coarse	23.33 (2.77)	.35 (.03)	.35 (.03)	.35 (.03)
			Fine	59.30 (6.45)	.37 (.04)	.37 (.04)	.37 (.04)
		MTvWS	Coarse	16.58 (2.16)	.36 (.03)	.36 (.03)	.37 (.03)
			Fine	47.09 (5.66)	.34 (.04)	.34 (.04)	.39 (.04)
Overwatch (Basketball Novices)							
	Overwatch	HOUvBOS	Coarse	7.33 (1.33)	.05 (.03)	.05 (.03)	.18 (.02)
			Fine	38.67 (16.29)	.14 (.01)	.14 (.01)	.41 (.02)
		LONvFLA	Coarse	10.33 (3.93)	.12 (.03)	.12 (.03)	.13 (.03)
			Fine	25.67 (7.31)	.03 (.02)	.03 (.02)	.17 (.01)
	Basketball	MEMvUCLA	Coarse	13.67 (1.33)	0.31 (.09)	.31 (.07)	.32 (.06)
			Fine	53.67 (13.12)	.32 (.03)	.44 (.03)	.44 (.01)
		MTvWS	Coarse	12.33 (3.93)	.21 (.06)	.39 (.10)	.38 (.09)
			Fine	53.00 (14.42)	.32 (.05)	.42 (.09)	.48 (.09)
Overwatch (Any Basketball Score)							
	Overwatch	HOUvBOS	Coarse	13.56 (3.76)	.11 (.04)	.11 (.04)	.21 (.06)
			Fine	30.56 (6.75)	.28 (.04)	.28 (.04)	.35 (.03)
		LONvFLA	Coarse	10.63 (4.24)	.07 (.04)	.07 (.04)	.10 (.05)
			Fine	36.00 (11.16)	.22 (.04)	.22 (.04)	.19 (.03)
	Basketball	MEMvUCLA	Coarse	23.33 (7.17)	.36 (.05)	.42 (.03)	.43 (.03)
			Fine	60.78 (17.39)	.23 (.07)	.36 (.08)	.37 (.09)
		MTvWS	Coarse	19.00 (6.32)	.36 (.05)	.47 (.04)	.45 (.05)
			Fine	41.56 (9.51)	.33 (.09)	.34 (.07)	.42 (.10)
Overwatch (Combined)							
	Overwatch	HOUvBOS	Coarse	12.00 (2.91)	.09 (.03)	.09 (.03)	.20 (.05)
			Fine	32.58 (6.17)	.25 (.03)	.25 (.03)	.36 (.02)
		LONvFLA	Coarse	10.55 (3.16)	.09 (.03)	.09 (.03)	.11 (.03)
			Fine	33.42 (8.50)	.17 (.04)	.17 (.04)	.19 (.02)
	Basketball	MEMvUCLA	Coarse	20.92 (5.45)	.35 (.04)	.39 (.03)	.40 (.03)
			Fine	59.00 (13.18)	.26 (.05)	.38 (.06)	.39 (.07)
		MTvWS	Coarse	17.33 (4.82)	.32 (.04)	.45 (.04)	.43 (.04)
			Fine	44.42 (7.81)	.33 (.06)	.36 (.06)	.43 (.08)
Controls (Novices)							
	Overwatch	HOUvBOS	Coarse	17.80 (2.85)	.24 (.02)	.19 (.02)	.27 (.02)
			Fine	29.84 (3.45)	.30 (.02)	.25 (.02)	.31 (.02)
		LONvFLA	Coarse	17.12 (2.47)	.12 (.02)	.07 (.01)	.14 (.02)
			Fine	34.71 (4.76)	.12 (.01)	.10 (.01)	.14 (.01)
	Basketball	MEMvUCLA	Coarse	28.64 (5.94)	.23 (.02)	.27 (.02)	.28 (.02)
			Fine	39.96 (3.65)	.40 (.03)	.34 (.03)	.38 (.03)
		MTvWS	Coarse	17.24 (2.10)	.28 (.02)	.29 (.02)	.30 (.02)
			Fine	34.89 (3.24)	.40 (.03)	.31 (.03)	.40 (.03)
Intermediates							
	Overwatch	HOUvBOS	Coarse	15.98 (1.93)		.16 (.02)	.26 (.02)
			Fine	36.92 (6.77)		.23 (.02)	.29 (.02)

	LONvFLA	Coarse	17.75 (3.48)		.07 (.01)	.15 (.02)
		Fine	41.79 (6.80)		.11 (.02)	.15 (.02)
Basketball	MEMvUCLA	Coarse	21.42 (2.70)		.28 (.02)	.29 (.02)
		Fine	53.94 (6.12)		.31 (.03)	.32 (.03)
	MTvWS	Coarse	18.90 (4.71)		.28 (.03)	.28 (.03)
		Fine	35.66 (4.09)		.26 (.03)	.33 (.03)

Note: Standard error in parentheses. With respect to Segmentation Agreement: Own = Compared to own group; Expert = Compared to expert group; Everyone = Compared to everyone.

Table 16. Hierarchical Alignment by All Groups

Hierarchical Alignment by Expertise Group

	Activity	Video	Temporal Distance	Enclosure
Basketball Experts				
	Overwatch	HOUvBOS	.11 (.04)	.47 (.18)
		LONvFLA	.12 (.03)	.47 (.19)
	Basketball	MEMvUCLA	.22 (.03)	.56 (.03)
		MTvWS	.26 (.04)	.57 (.04)
Overwatch (Basketball Novices)				
	Overwatch	HOUvBOS	.26 (.16)	.58 (.13)
		LONvFLA	.09 (.02)	.51(.20)
	Basketball	MEMvUCLA	.27 (.08)	.57 (.15)
		MTvWS	.30 (.16)	.56 (.09)
Overwatch (Any Basketball Score)				
	Overwatch	HOUvBOS	.37 (.15)	.46 (.04)
		LONvFLA	.31 (.09)	.43 (.07)
	Basketball	MEMvUCLA	.38 (.06)	.61 (.08)
		MTvWS	.57 (.12)	.64 (.08)
Controls (Novices)				
	Overwatch	HOUvBOS	.11 (.04)	.41 (.03)
		LONvFLA	.05 (.03)	.45 (.03)
	Basketball	MEMvUCLA	.23 (.03)	.45 (.03)
		MTvWS	.31 (.04)	.49 (.03)
Intermediates				
	Overwatch	HOUvBOS	.12 (.05)	.43 (.03)
		LONvFLA	.14 (.04)	.51 (.03)
	Basketball	MEMvUCLA	.19 (.03)	.51 (.03)
		MTvWS	.22 (.05)	.49 (.03)

Note: Standard error in parentheses.

Table 17. Memory Performance by All Groups

Memory Performance by Expertise Group

	Activity	Video	Recognition	Order
Basketball Experts				
	Overwatch	HOUvBOS	11.68 (.52)	4.41 (.26)
		LONvFLA	12.03 (.51)	4.41 (.27)
	Basketball	MEMvUCLA	12.53 (.51)	3.94 (.22)
		MTvWS	14.65 (.55)	4.21 (.28)
Overwatch (Basketball Novices)				
	Overwatch	HOUvBOS	16.33 (2.33)	6.00 (.00)
		LONvFLA	15.00 (1.15)	4.67 (1.20)
	Basketball	MEMvUCLA	11.00 (1.15)	4.00 (1.00)
		MTvWS	8.67 (2.19)	3.33 (.67)
Overwatch (Any Basketball Score)				
	Overwatch	HOUvBOS	16.67 (1.05)	5.67 (.65)
		LONvFLA	15.44 (.85)	6.33 (.47)
	Basketball	MEMvUCLA	11.22 (1.21)	3.56 (.38)
		MTvWS	15.56 (.82)	3.78 (.76)
Overwatch (Combined)				
	Overwatch	HOUvBOS	16.58 (.92)	5.75 (.48)
		LONvFLA	15.33 (.68)	5.92 (.48)
	Basketball	MEMvUCLA	11.17 (.93)	3.67 (.36)
		MTvWS	13.83 (1.18)	3.67 (.58)
Controls (Novices)				
	Overwatch	HOUvBOS	11.00 (.30)	4.58 (.18)
		LONvFLA	12.62 (.31)	4.33 (.17)
	Basketball	MEMvUCLA	10.57 (.23)	4.35 (.18)
		MTvWS	11.72 (.38)	3.95 (.23)
Intermediates				
	Overwatch	HOUvBOS	12.02 (.40)	4.32 (.20)

	LONvFLA	12.89 (.41)	4.67 (.22)
Basketball	MEMvUCLA	11.69 (.30)	4.27 (.22)
	MTvWS	13.43 (.38)	3.67 (.21)

Note: Standard error in parentheses.