2018

Event segmentation and expertise

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ABSTRACT

EVENT SEGMENTATION AND EXPERTISE

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Events are composed of component parts (i.e., sub-events) and humans naturally recognize shifts between events and sub-events. The process of chunking continuous spatiotemporal information into meaningful discrete parts during encoding is known as event segmentation. Research suggests that segmentation is driven by perceptual change, in a bottom-up fashion, rather than by background knowledge, in a top-down fashion. However, much of the previous work has focused on segmentation in contexts where there is likely to be minimal variation in one's level of background knowledge (e.g., washing the dishes). The goal of the present study was to explore the extent to which domain knowledge affects the segmentation and interpretation of events. In Experiment 1, participants watched basketball clips that were more or less structured in nature and provided ratings on the extent to which gameplay was structured, unstructured, strategic, and contained plays. In Experiment 2, participants watched clips from Experiment 1 and engaged in a segmentation task followed by an event description task. Domain knowledge did not appear to affect event segmentation but did affect video ratings in Experiment 1 and event descriptions in Experiment 2. Results suggest that segmentation is largely driven by perceptual change with knowledge affecting later processing. While results are consistent with prior research, they are not definitive. The issue of whether or not prior knowledge affects early encoding processes and segmentation remains an open question and further research is needed to explore this issue. Implications, potential limitations, and suggestions for future work are discussed at length.

NORTHERN ILLINOIS UNIVERSITY
DEKALB, ILLINOIS

AUGUST 2018

EVENT SEGMENTATION AND EXPERTISE

BY

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A THESIS SUBMITTED TO THE GRADUATE SCHOOL

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE

MASTER OF ARTS

DEPARTMENT OF PSYCHOLOGY

Thesis Director:
Joseph P. Magliano

ACKNOWLEDGEMENTS

I would like to acknowledge my committee members Katja Wiemer, Stephan Schwann, and Joe Magliano for all of their help, advice, and support. I learned so much from each of you and the project truly is truly better thanks to your contributions. I would also like to acknowledge my lab mates. You all answered countless questions, helped with E-Prime, or motivated me when things got tough. I wouldn’t be where I am today with out you guys. Lastly, I would like to thank my beautiful wife and children for their patience, love, and endless support.

DEDICATION

I dedicate this thesis to my family. What a crazy ride it's been. There is no greater motivation than those who you care most deeply about and that is each of you. You've each inspired and pushed me to grow beyond what I thought I was capable of. You are the passion behind all my other passions.

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CHAPTER 1

INTRODUCTION

The year was 2012 and rivals Duke and North Carolina were battling for the top spot in college basketball. Duke had trailed the entire game but got the ball, down by two, with 10 seconds left on the clock. Austin Rivers calmly ran the ball past half court. Then, just before time expired and the buzzer sounded, he heaved a shot up from well behind the 3-point line. Swish. Duke wins and the crowd goes wild. This description may reflect how someone less familiar with basketball might perceive and remember the final play of the game; Duke star, Austin Rivers, merely dribbled down the court and hit a big shot when they needed it. However, to true basketball fans, something pivotal happened well before Rivers squared up to shoot the 3. With several seconds left, Duke big-man Mason Plumlee ran up and set a high-ball screen (i.e., created an impasse) on the defender guarding Rivers. As a result, the defense was forced to switch defenders, leaving a bigger, slower defender on the smaller, quicker point-guard. Having got the defense right where they wanted them, Rivers' teammates spread the floor, giving him space to exploit the mismatch. The defender likely didn't want Rivers to run past him and was forced to give him a little extra space, which enabled him to use the space to hit the game-winner.

The example above illustrates two points. First, it demonstrates that people may perceive events, such as the one described, as being made up of a series of sub-events (Kurby & Zacks, 2008; Newtson, 1973). For example, one might perceive the game itself to be an event, however, the game consists of various sub-events (e.g., quarters, possessions, plays, etc.). There is substantial literature suggesting that people habitually segment events into their discrete component parts and that memory for events is organized around this perceived structure (e.g., Newtson, 1973; Radvansky & Zacks, 2011; Zacks, Speer, Vettel, & Jacoby, 2006). The process of chunking the ever-present, continuous stream of information into meaningful events is known as event segmentation (Kurby & Zacks, 2008).

Secondly, the example shows the importance of background knowledge in perceiving and understanding events. Those with less basketball knowledge likely failed to notice what an expert might call a critical event—namely, the play that set up the final shot. Thus, prior knowledge may affect the way in which we view events. Indeed, research has shown that background knowledge may affect encoding and memory processes in a number of ways (e.g., Chase & Simon, 1973; Voss, Vesonder, & Spilich, 1980).

While prior knowledge and expertise are known to affect comprehension and memory processes, the role of expertise in event cognition is less understood (Zacks, Tversky, & Iyer, 2001; Zacks, Kumar, Abrams, & Mehta, 2009). As seen through the example provided, it seems plausible that one's prior knowledge could play a role in the way in which an event is viewed. However, there are several questions to consider. For example, does domain knowledge exert an effect early on, affecting segmentation and perceptual processes? Or does it have its influence later on, affecting event interpretation and other processes downstream? To date, research on this matter has remained mixed and inconclusive. While there is some evidence supporting the idea that background knowledge helps one structure event perception hierarchically (e.g., Zacks et al., 2001a), other evidence suggests that background knowledge has no effect on event segmentation (e.g., Zacks et al., 2009). As will be argued below, there may be aspects of these studies that limit the role expertise is allowed to have in the context of the experimental tasks.

The goal of this thesis was to explore the extent to which an expert's domain knowledge affects the segmentation and subsequent interpretation of an event. In doing so, this thesis informs current theory regarding how we segment events into sub-events, and in particular Event Segmentation Theory (Zacks, Speer, Swallow, Braver, & Reynolds, 2007). In the following sections, research on event segmentation and prior knowledge will be briefly summarized in order to provide necessary background information. The motivation and justification for the study will then be presented.

CHAPTER 2

LITERATURE REVIEW

In this chapter, event segmentation and Event Segmentation Theory will be described and discussed. Assumptions of the theory will be outlined and evidence supporting these assumptions will be provided. After providing evidence for the importance of background knowledge in various domains, the argument will be made that research is needed to further explore the role of background knowledge and expertise in event segmentation. This section will conclude with a brief overview of the current study.

Event Segmentation

Events are composed of component parts (i.e., sub-events) and humans are easily able to recognize shifts between events and sub-events. For example, when washing the dishes, a person will alternate between scraping off the plates to washing the plates, and from washing the plates to placing them in the dish rack. Research shows that people tend to agree on what components make up everyday events (Bower, Black, & Turner, 1979; Zacks & Tversky, 2001). The process of chunking the continuous spatiotemporal stream of information into discrete parts during encoding is called event segmentation (Kurby & Zacks, 2008).

In a seminal study on event segmentation, Newtson and Engquist (1976) had participants watch short films of people performing simple goal directed activities (e.g., completing a questionnaire) and segment them into distinct events. Researchers found that there was high agreement in the segmentation of events and that disagreement was generally due to stable individual differences rather than error. There is strong evidence that segmentation operates when experiencing complex goal directed behaviors that occur in the context of everyday events (e.g., Zacks et al., 2006; Zacks et al., 2001a), narrative experiences (Kurby & Zacks, 2012; Magliano et al., 2001; 2005; 2011; Schwan & Garsoffky, 2004; Zacks et al., 2009), and first person video gameplay (Magliano, Radvansky, Forsythe, & Copeland, 2014). In the context of these tasks, there is remarkable regularity in the locations where people segment, which is called segmentation agreement. Zacks and colleagues have shown agreement by parsing videos of events into time bins (e.g., one second bins), calculating the proportion of participants who made segmentation judgments in those bins, and then correlating individual participant's judgments against a normative representation of judgments (Speer, Swallow, & Zacks, 2003; see also Zacks et al., 2006).

Segmentation occurs on different levels of specificity, which has been shown in the context of a fine and coarse grain segmentation task (Newtson, 1973; Speer et al., 2003; Zacks et al., 2001a). In a fine grain task, participants are asked to make segmentation judgments in terms of the smallest meaningful events, whereas coarse grain judgments are made considering the largest meaningful judgments. These judgments appear to be hierarchically nested, such that fine-grained judgments occur within coarse-grained judgments. Studies have shown that event segmentation ability is remarkably consistent both between and within people over time (Speer et al., 2003). Others too have noted the striking agreement in unit boundaries (Zacks et al., 2001a).

Importantly, event segmentation appears to be a natural, habitually occurring phenomenon. Using functional magnetic resonance imagery (fMRI), Zacks and colleague have found a segmentation network that is involved when viewers actively engage in a segmentation task while viewing videos of everyday activities and when watching those videos passively (Speer, Zacks, & Reynolds, 2007; Zacks et al., 2001b)(see also Whitney et al., 2009 for similar evidence involving reading). The frontal eye field (FEF), MT complex, and anterior cingulate cortex (ACC) are most correlated with event boundaries and prediction error (Spear et al., 2003; Zacks et al., 2007). The FEF and MT complex are important structures associated with motion processing (Spear et al., 2003).

Why does segmentation matter psychologically? Research has shown that event segmentation has important implications for various aspects of cognition. For example, event segmentation has been strongly linked to learning and memory (Bailey, Kurby, Giovannetti, & Zacks, 2013; Ezzyat & Davachi, 2011; Kurby & Zacks, 2011; Sargent et al., 2013; Zacks et al., 2006). Research indicates that people who segment information from an event more closely to the norm will have better memory for that event at a later time, regardless of individual differences in general cognitive abilities (Sargent et al, 2013; Zacks et al., 2006). Thus, event segmentation appears to be a basic, independent aspect of event memory, uniquely predicting memory in both younger and older adults alike (Sargent et al., 2013).

Other research has emphasized the importance of segmentation in encoding processes and event recall. For example, research suggests that one's memory for an event declines once an event boundary is crossed (i.e., a new event is started; Radvansky & Copeland, 2006; Radvansky, Krawietz, & Tamplin, 2011; Radvansky, Tamplin, & Krawietz, 2010; Schwan & Garsoffky, 2004; Schwan, Garsoffky, & Hesse, 2000). This effect was demonstrated in a study by Schwan & Garsoffky (2004). In this study, researchers had participants view film clips that had short deletions placed either at or in between event boundaries. When asked to recall the movies, memory for films with deletions at event boundaries was poor while memory for films with deletions in between event boundaries was largely unaffected by the deletions. Some speculate that the ability to segment information is a form of chunking, allowing information to be organized into larger units to decrease cognitive load (Kurby & Zacks, 2008).

Event Segmentation Theory (EST)

Event Segmentation Theory was proposed in order to explain how humans perceive and understand events as they unfold over time (Zacks et al., 2007). The theory was originally intended to account for the perception of continuous events, particularly those of other people, but has also been applied to the perception of one's own actions (Magliano et al., 2014). EST has become a prominent theory in research pertaining to event cognition and segmentation.

One assumption of EST is that event models are built to enable the comprehension of an event (Magliano et al., 2014). An event model is a cognitive representation of what is happening in the moment, maintained in working memory, and is related to situation models (see Radvansky & Zacks, 2011, 2014; Zwaan & Radvansky, 1998). According to EST, people use event models to make predictions about the continuity of events in the immediate future (Kirby & Zacks, 2008). A second assumption of EST is that instability in an event model emerges from prediction error, which arises when perceptual information does not match the prediction generated by the event model (e.g., a hand moving forward stops moving forward). Once an error threshold is met and incoming information can no longer be integrated into the existing event model, a new event model is created and an event boundary is perceived. At event boundaries, the brain engages in large scale updating, wherein information from the previous event model is encoded into long-term memory and a new event model is created based on information from the environment, wherein prediction again becomes accurate. The presence of an event boundary serves as an indicator that a new event or sub-event has begun (see Kirby & Zacks, 2008; Zacks et al., 2007 for review). Updating an event model happens at different scales (Kurby & Zacks, 2008; Kurby & Zacks, 2012). Incremental updating occurs when small event changes are mapped onto existing event models (Kurby & Zacks, 2012; see also Gernsbacher, 1990; Zwaan & Radvansky, 1998). This allows one to maintain a relatively stable event model despite changes to situational features (Kurby & Zacks, 2012). Global updating, on the other hand, occurs in the face of mounting prediction error and results in an event model being updated as a whole (Kurby & Zacks, 2012; Zacks et al., 2007).

A third and critical assumption of the model is that event models are gated, such that prior knowledge affects them primarily when event boundaries are perceived. Thus, it is at event boundaries that prior knowledge, schemas, or scripts are used to aid in the creation of a new event model (Kurby & Zacks, 2008). While small scale, incremental updating is largely thought be immune to the influence of topic knowledge and expertise, it is principally during large scale updating (i.e., during gating) that event models are considered to be more susceptible to the effects of prior knowledge and expertise. Thus, while both incremental and global updating are thought to be influenced by perceptual features, in a bottom-up fashion, only during global updating are conceptual influences thought to take effect in a top-down fashion (Kurby & Zacks, 2012).

A fourth assumption arises from the previous assumption. Since prior knowledge is assumed to take its effect at gating, the process of segmentation is assumed to be predominantly affected by perceptual change. Thus, while EST acknowledges that event boundaries can result from conceptual change, in a top-down fashion, EST places special emphasis on the role of perceptual change in event segmentation.

A number of studies provide support for the EST assumption that segmentation supports the understanding of everyday events. Individuals who segment everyday activities more closely to the norm tend to have better memory for events later on (Kurby & Zacks, 2011; Sargent et al., 2013; Zacks et al., 2006). As mentioned above, segmentation ability appears to be a unique predictor of memory performance when accounting for other general cognitive abilities (Sargent et al., 2013). Furthermore, there is evidence that suggests that the ability to segment everyday activities is related to one's performance of such activities (Bailey et al., 2013).

There is a growing body of research suggesting that event segmentation supports the processing of narrative experiences (Kurby & Zacks, 2012; Magliano, Kopp, McNerny, & Radvansky, 2012; Magliano, Miller, & Zwaan, 2001; Magliano & Zacks, 2011; Zacks et al., 2009). However these studies have typically shown that shifts in situational continuity (e.g, space, time, causality), rather than prediction error, are predictive of segmentation behavior, which could involve backward mapping processes rather than prediction (e.g., Zwaan & Radvansky, 2001). As such, the extent that these studies are consistent with the assumption that prediction error is necessary for segmentation may be questionable.

Additional support for EST and the prediction assumption comes from studies that demonstrate that updating occurs in response to prediction failure (e.g., Kurby & Zacks, 2012; Whitney et al., 2009; Zacks et al., 2007). In one study, Zacks, Kurby, Eisenberg, and Haroutunian (2011) had participant watch movies of everyday events. Movies were paused once per minute and participants were asked to make predictions about what would happen 5 seconds later. Results showed that predictions were slower and less accurate when participants were asked to make a prediction that spanned an event boundary. Furthermore, areas of high unpredictability corresponded closely to subjective event boundaries.

There is also growing evidence that segmentation appears to be gated from prior knowledge such that it appears to be mostly affected by lower level changes and bottom-up processes. For example, Zacks and colleagues (2009) examined the effect of conceptual framing on segmentation. In this study, participants viewed films of everyday events. For each film, a simple animation was constructed from motion sensors on the actor's hands and head. Thus, videos were stripped of visual information and were left only with an animation representing the actions of the actor's head and hands. In one condition (animation-informed), participants watched 40 seconds of the un-impoverished film before the film was reduced to a simple animation. This was intended to allow participants to contextually frame the video and activate a schema for the activity. In the other condition (animation-uninformed), participants watched only the reduced animation film. Contrary to the researchers hypotheses, results showed no difference in segmentation between the animation-informed and uninformed conditions.

Additionally, Hard, Tversky, and Lang (2006) looked at event segmentation in relation to knowledge of an actor's intentions and goals. In their study, participants segmented short, abstract films of animated objects. Experimenters manipulated whether films were novel or familiar and whether they were viewed forward or backward. Despite interpreting both forward and familiar films as more intentional in a think-aloud task, there was no difference in segmentation between groups. These results suggest that viewers based their segmentation of films on physical, perceptual changes alone. Only the after-the-fact interpretation task was influenced by the experimental conditions. In this study, researchers concluded that event segmentation is a bottom-up process that functions independent of an understanding of the activity and an actor's goals and intentions. Thus, "perceiving event structure appears to enable event schemas, rather than resulting from them" (Hard et al., 2006, pg. 1221).

Other research has examined the role of background knowledge in segmentation by manipulating familiarity and level of expertise. In one study (Zacks et al., 2001a), researchers had participants watch and segment videos of familiar (e.g., washing the dishes) and unfamiliar (e.g., assembling a saxophone) everyday events. Segmentation for videos depicting familiar activities was more hierarchically structured than for videos of less familiar activities. Follow-up studies, however, failed to magnify this familiarity effect manipulating background knowledge and expertise. In one experiment, participants were either trained or untrained in the assembly of a saxophone, while in another experiment, participants were either experts or novices at the activity. Results showed no significant differences in segmentation between trained and untrained or expert and novice participants. Thus, while there was some evidence for a "familiarity effect" that was hypothesized to result from the activation of event schemata, this effect was not pronounced by further experimental manipulation.

The dearth of evidence supporting the effect of prior knowledge on segmentation may result from aspects of the experimental tasks used in previous studies. In the majority of the studies mentioned, researchers used simple animations or short films of everyday activities (e.g., folding laundry, making a sandwich) for which extensive background knowledge and expertise are nullified (e.g., Hard et al., 2006; Zacks, 2004; Zacks et al., 2009). It may be that perceptual change is sufficient to drive segmentation in these contexts. Moreover, studies manipulating familiarity and expertise may have used events that were too common or well-known. On this note, Zacks and colleagues (2001a) acknowledge that the event used in their unfamiliar condition (i.e., assembling a saxophone) may not have been novel enough to elicit an effect since most people have ample experience assembling other objects. It is also important to understand that EST was originally intended to account for segmentation behavior in relatively simple events with single actors. The theory may or may not be adaptive to more complex scenarios where attention is divided and multiple actors interact. In the present study, it is proposed that materials that highlight drastic differences in domain knowledge and expertise be used in order to ensure varying activation levels of event schemata and prior knowledge. Further, it is proposed that complex events, involving several actors be used to see the extent to which EST applies to such events more broadly.

In regard to segmentation and expertise, Magliano, Radvanksy, Forsythe, and Copeland (2014) recommended the use of dynamic events in which rules and goal structures may be somewhat ambiguous to novices. Since sporting events are highly structured and event knowledge is likely to vary largely from person to person, it is proposed that short basketball clips be used to test the role of expertise in event segmentation. Previous research in expertise has often used sports as a medium. Voss and colleagues (1980) used baseball to study the effects of expertise on aspects of memory (see below), while Sneider, Körkel, and Weinert (1990) used soccer in a similar study. Other research has shown that dance experts have shorter eye fixations and faster saccades than novices when viewing a performance, supporting the idea that experts and novices view sports differently (Stevens et al., 2010).

Prior Knowledge and Expertise

While the role of prior knowledge and expertise in event segmentation is less understood, domain specific knowledge has pronounced effects on memory and comprehension (e.g., Spilich, Vesonder, Chiesi, & Voss, 1979; Voss et al., 1980). In a seminal study by De Groot (1978), experts in chess were shown to have higher recall for the positions of chess pieces on a board than novices. Chase and Simon (1973) extended this finding, showing that master chess players demonstrated different perceptual and memory processes than chess novices. Interestingly, this effect was dependent upon the structure and formation of the game pieces. When chess pieces occupied legal and natural formations, like those found in gameplay, experts had higher recall than novices. However, there were no significant differences between experts and novices when chess pieces were placed in random, unnatural formations. Researchers concluded that the amount of information that can be extracted from a given situation is dependent upon the degree of expertise of a player as well as the structure of the information. Interestingly, Allard, Graham, and Paarsalu (1980) replicated this finding using basketball experts. In their study, experts were better at recalling and recognizing pictures of basketball formations than non-experts, but this effect was specific to structured gameplay (e.g., pictures representing offensive plays in progress) and not unstructured gameplay (e.g., pictures representing a turnover or rebound). While these studies were instrumental in shaping the present study, it is important to be clear that they focused on the role of expertise in regard to static images, not videos. In this sense, the present work also seeks to extend these findings to a new medium.

Other research has emphasized the importance of domain knowledge in comprehension (Bransford & Johnson, 1972; Long & Prat, 2002; Spilich et al., 1979; Voss et al., 1980). For example, in one study, Spilich and colleagues (1979) had participants with high and low domain knowledge of baseball listen to half an inning of a baseball game and engage in a recall task. Results showed that high knowledge participants recalled more about the inning, especially when information was related to goal structures. In a similar study, Voss, Vesonder, and Spilich (1980) showed that those who were relatively unfamiliar with baseball seemed to have trouble connecting sub-goals to the main goal. This lead to poorer recall for novices compared to experts (see also Schneider et al., 1990). Results of this ilk suggest that experts see events as a series of episodes based around an overarching goal structure and that this facilitates information encoding and retrieval (Spilich et al., 1979).

As noted, the effects of prior knowledge and expertise on comprehension and memory processes are well established (e.g., Long & Prat, 2002; Spilich et al., 1979; Voss et al., 1980). But what role might prior knowledge play in the perception and comprehension of events? Research on sports expertise may lend insight to this question. For athletes, knowing when and where to look is an essential aspect of successful performance in a sport (Mann, Williams, Ward, & Janelle, 2007). Experts in sports must learn to direct their attention toward important details of a scene (or film) and extract the most meaningful information as efficiently and effectively as possible (Mann et al., 2007; Williams, Davids, & Williams, 1999). As such, it has been proposed that experts use their knowledge to help facilitate encoding processes and make them more efficient (Herzman & Curran, 2011; Rawson & Van Overschelde, 2008). Results from a meta-analysis examining expertise in sports confirm this proposition and suggest that there are differences between experts and novices both in their visual search behaviors and in the accuracy and response times they produce to stimuli (Mann et al., 2007). According to Mann and colleagues (2007), experts were consistently shown to have fewer eye fixations of longer duration than novices. Furthermore, experts were consistently faster and more accurate at picking up perceptual cues in all studies analyzed (for references specific to basketball see Laurent, Ward, Williams, & Ripoll, 2006; Ripoll, Baratgin, Laurent, Courrieu, & Ripoll, 2001). Part of this may be due to the fact that experts must anticipate and predict their opponent’s actions in order to enhance their performance (Abreu et al., 2012; Araujo, Davids, Hristovski, 2006). The ability of experts to anticipate and predict upcoming events (Abernethy, 1988; French & Thomas, 1987; Mann et al., 2007; McPherson, 2000; Starks, 1987) may be critical for segmentation behavior. Given that EST assumes prediction error to be the driving force for updating, experts should have an enhanced ability to make more accurate predictions, thus allowing them to maintain stable event models over longer periods of time. This should be especially true of structured gameplay that adheres to prototypical schemas that experts have developed. Thus, here it is argued, as it has been previously, that "when processing an event, attention may be guided by conceptual expectations, prior experience with that class of event, or perceptual characteristics of part of the event that have unfolded so far" (Zacks & Tversky, 2001, p. 16).

The Current Study

In previous sections, event segmentation, EST, and the role prior knowledge plays in various domains were each discussed. Based on this discussion, it seems that the question may not be *if* prior knowledge plays a role in event perception but *when* and *how* it plays a role and exercises it's effects. It may be the case that event segmentation is primarily affected by lower level prediction error, as assumed by EST, and therefore prior knowledge does not affect segmentation. Rather, it would affect the updating of an event model (in working memory) and the resultant mental model (in episodic memory). If this is the case, then prior knowledge would primarily play a role in the interpretative processes that support mental model construction (e.g., Graesser, Singer, & Trabasso, 1994). However, it is also possible that, under the right conditions, event segmentation could be influenced by prior knowledge. The example basketball play described at the outset of Chapter 1 hints at this possibility. As was argued in the last section, it may be the case that the materials used in prior studies minimize the role or need for prior knowledge to support segmentation.

The goal of this thesis is to explore the role of prior knowledge in the segmentation and interpretation of complex events that require prior knowledge to fully understand. In the present study, short basketball clips were used in an attempt to have participants activate relevant event knowledge and schemata. The aim of Experiment 1 was to verify the extent that high and low knowledge individuals differed in their sensitivity to gameplay structure when watching basketball. Participants with a range of basketball knowledge watched a series of basketball clips and rated them on the extent to which they were structured. Similar to Chase and Simon's (1972) seminal study of chess expertise, the structure of the gameplay varied. That is, some clips contained mostly well-defined plays (e.g., pick-and-roll) while others contained gameplay in which no clear plays were being executed. If high and low knowledge individuals differ in their sensitivity to gameplay type, there may be differences in segmentation as well. Experiment 2 aimed to verify whether or not there were differences in the early encoding processes of high and low knowledge individuals. Participants watched basketball clips from Experiment 1 and engaged in an event segmentation task. Segmentation frequency and agreement were measured, with agreement being the primary dependent measure (Kurby & Zacks, 2012; Zacks et al., 2006).

CHAPTER 3

EXPERIMENT 1

The purpose of Experiment 1 was two-fold: 1) to test the reliability and validity of an instrument designed to differentiate between people with high and low basketball knowledge (i.e., the Basketball Domain Knowledge Questionnaire) and 2) to ensure that the manipulation of structure in basketball videos, as assessed by the intuition of the experimenter, was perceived and recognized by people with a high degree of basketball knowledge. To achieve these goals, online participants viewed basketball videos and rated them on several dimensions reflecting the structure of the gameplay. The domain knowledge instrument was also administered.

With respect to the Basketball Domain Knowledge Questionnaire, the instrument was anticipated to be reliable to the extent that it shows a high degree of internal consistency. Specifically, a Cronbach's alpha value of 0.70 or higher was expected, as this is typically regarded as the acceptable standard (e.g., Tavakol & Dennick, 2011). In terms of validity, the validity of the instrument will be tested by examining the extent to which high and low knowledge individuals respond to the manipulation of structure. Specifically, participants with high scores on the Basketball Domain Knowledge Questionnaire were expected to differentiate between high and low structured items to a greater degree than participants with low scores.

In order to examine the validity of the manipulation of structure in gameplay footage, participants' level of basketball knowledge in relation to their ratings of structure will again be examined. Participants with higher levels of basketball knowledge should perceive more structure for structured clips than the unstructured clips. Specifically, participants with high scores on the Basketball Domain Knowledge Questionnaire were anticipated to rate structured items with higher scores than unstructured items. Lastly, it should be noted that the validity of the manipulation of structure and the validity of the questionnaire are dependent upon one another. That is, in order for both the manipulation and questionnaire to be valid, participants with higher scores on the questionnaire must perceive structured gameplay to be more structured than unstructured gameplay, whereas, for the questionnaire to be valid, participants with higher scores on the questionnaire must perceive more structure for the structured materials than participants with lower scores.

Methods

Participants

Amazon's Mechanical Turk (MTurk) website was used to recruit 51 online participants for the study. MTurk has been used in cognitive research and has been validated for such purposes (see Germine et al., 2012; Poalacci, Chandler, & Ipeirotis, 2010). Participants (N = 51, 66% male, mean age = 34.5) were compensated $1.00 for their participation in the study.

Design

A within-participants design was used with gameplay type (more structured, less structured) as the independent variable. Ratings on the degree to which videos were structured, unstructured, strategic, and contained plays served as dependent variables (i.e., scores for each of these measures were aggregated across videos). A linear mixed effect model was used in order to examine differences in ratings of structured and unstructured videos for participants with a varying degree of domain knowledge.

Materials

Basketball Domain Knowledge Questionnaire

An adapted version of a questionnaire developed by French & Thomas (1987) was use in the current study. This scale was previously shown to be reliable (alpha = .86) in an adolescent population. Here, a small sub-set of items was adapted to better serve an adult population. The questionnaire consisted of 10 multiple-choice items with questions addressing terminology, strategy, and general principles of the game (see Appendix A). In the current study, the reliability of the instrument was found to be acceptable (Cronbach's alpha = .78).

Basketball Videos

Basketball clips were taken from high-quality YouTube videos of NCAA Division One basketball games. Gameplay was selected based on the amount of structured play it contained, as determined by the experimenter and in consultation with expert colleagues. In order to aid in the selection of gameplay, a checklist was created wherein basic components of basketball plays were identified and listed. While creating an exhaustive list of the numerous plays and variants of plays that any given basketball team might engage in would prove to be difficult, creating a checklist that identified basic components, common to most plays, was a feasible task. Both offensive and defensive gameplay was considering in constructing the checklist (see Table 1).

Table 1

Checklist of Basic Components of Plays Used to Select Materials

Offense	Defense
Screen (or Pick)	Switch
Roll	Zone
Post-up	Double-team
Cut	Mismatch

Generally speaking, structured gameplay contained long stretches of mostly orderly play, wherein multiple set plays were being attempted or executed (e.g., pick and rolls, etc.), while less structured gameplay consisted of mostly unorganized play that was more improvised in nature (e.g., “run-and-gun” offense, fast-breaks, etc.). There were 12 videos total (6 structured, 6 unstructured). Videos were matched on length so that each structured video was within a few seconds of an unstructured video in length. Video clips ranged from approximately 60 to 175 seconds with a mean length of 70.67 seconds. Independent-samples t-tests showed that structured (M = 70.17, SD = 19.71) and unstructured (M = 71.17, SD = 22.30) videos did not statistically differ by length, $t(10) = -0.08$, p = 94. However, videos did statistically differ in the number of shot attempts, possession changes, and plays they contained (see Table 2). Less structured videos contained more shot attempts and possession changes while structured videos contained more plays. This makes sense given the nature of game. The type of gameplay found in less structured videos (e.g., run and gun offense, fast breaks) often results in a faster tempo with more shot attempts and possession changes. On the other hand, the fact that structured gameplay contained more set plays confirms the intended design and criteria upon which videos were selected.

Table 2

Content Analysis Comparing Structured and Unstructured Videos

	Structured		Unstructured		
	M	*SD*	*M*	*SD*	*t-test*
Passes	12	3.74	14.33	4.55	.971
Shot Attempts	2.83	.983	4.67	1.51	2.50*
Baskets Made	1.5	.837	2.67	1.97	1.34
Possession Changes	2	.632	4.17	1.33	3.61*
Fouls	0.5	.548	0.5	.548	0 .00
Plays	6.67	3.01	2.67	1.63	2.86*

* $p < .05$

Procedure

Upon completing an online informed consent, participants were instructed to watch video clips, paying attention to how much of the video contained structured, strategic gameplay, wherein plays were being executed or attempted. After viewing each video, participants were asked to rate them on the extent to which they contained structured gameplay, unstructured gameplay, strategic gameplay, and gameplay with plays being executed or attempted. Participants provided ratings to each of the four questions using a visual analog scale, ranging from “very little” to “a lot”. A practice trial was given in order to familiarize participants with the procedure.

After viewing and rating all 12 videos, participants completed the Basketball Domain Knowledge Questionnaire and a brief demographic questionnaire. Items in the Domain Knowledge Questionnaires were presented randomly. One trap question ("If you are paying attention and read this, please select answer "D") was included to ensure that participants were relatively engaged in the task. No participants were excluded based on this criterion.

Data Analytic Plan

In order to analyze the data, separate linear mixed effects models were fitted for each of the four dependent variables (degree to which gameplay was rated as structured, unstructured, strategic, and contained plays). Gameplay type was coded as 0, 1 for unstructured and structured videos, respectively. Gameplay type was added as an independent variable at level-1 while Domain Knowledge (DK) scores were added at level-2. Both Gameplay type and Domain Knowledge were entered as centered variables.

Results and Discussion

All analyses were performed using the lme4 package (Bates, Maechler, Bolker, & Walker, 2014) in R (R Core Team, 2013). The average domain knowledge score was 44% (*SD* = 0.27). Descriptive statistics are presented in Table 3. To start, a null mixed effects model for each of the four dependent variables was fitted. Ratings on the extent to which gameplay was structured, unstructured, strategic, and contained plays served as the outcome variable in each analysis, while item and subject were treated as random effects. These analyses revealed that significant variance in each of the dependent variables was accounted for by subject but not item (see Table 4 for intraclass correlation coefficient (ICC) and design effect (DEFF) values). Next, gameplay type (i.e., structured, unstructured) was added to each analysis as a level-1 predictor. In order to examine whether a participant's level of domain knowledge affected their perception of structure, domain knowledge scores were also added as a cross-level, level-2 predictor.

Table 3.
Means and Standard Deviations (parentheses) by Gameplay Type for Each Dependent Variable

	Gameplay Type	
	Structured	Unstructured
Structured	69.45 (19.0)	64.26 (22.52)
Unstructured	43.08 (26.60)	51.29 (27.50)
Strategic	68.21 (20.34)	63.15 (23.10)
Contained Plays	65.04 (21.45)	61.63 (24.33)

Table 4.
Intraclass Correlation Coefficients for each Dependent Variable. Design Effects (DEFF) are I included in Parentheses

	ICC	
	Subject	Item
Structured Ratings	.27 (3.92)	.03 (1.34)
Unstructured Ratings	.27 (3.92)	.03 (1.34)
Strategic Ratings	.24 (3.65)	.03 (1.34)
Contained Plays Ratings	.35 (3.65)	.01 (1.34)

Results indicated that gameplay type was a significant predictor of structured and unstructured ratings (p = .04, p < .001, respectively) but was only a marginally significant predictor of strategic and plays ratings (p = .06, p = .07, respectively). Similarly, domain knowledge was a significant predictor of structured ratings (p = .04) but was only a marginally significant predictor of strategic ratings (p = .08). Domain knowledge was not a significant predictor of unstructured and plays ratings (p = .20, p = 0.35, respectively). The interaction term (i.e., cross-level effect) was significant for each analysis (p < .001), suggesting that domain knowledge scores positively affected the effect of the L1 predictor (i.e., the slope of gameplay type). That is, as domain knowledge increased, the effect of gameplay type on ratings increased (see Table 5 for final model estimates)(see Table 6 for information on the interaction).

Table 5.

Model Estimates for each of the Final Linear Mixed Models

DV		Estimates	*SE*	*t*
Structured Ratings				
	Fixed Effects:			
	Intercept	66.85**	1.81	36.89
	Gameplay Type	2.60*	1.07	2.43
	DK Score	-3.46*	1.62	-2.13
	Gameplay*DK	3.76**	0.70	5.39
	Total R^2	.085		
	Random Effects:		*SD*	
	Subject	109.44	10.46	
	Item	7.84	2.80	
Unstructured Ratings				
	Fixed Effects:			
	Intercept	47.19**	2.61	18.06
	Gameplay Type	-4.15**	0.82	-5.01
	DK Score	-2.46	2.62	-0.94
	Gameplay*DK	-3.77**	0.82	-4.59
	Total R^2	.068		
	Random Effects:		*SD*	
	Subject	314.0	17.72	
	Item	0.0	0.0	
Strategic Ratings				
	Fixed Effects:			
	Intercept	65.69**	1.90	34.62

(Continued on next page)

Table 5 (continued)

	Gameplay Type	2.53-	1.19	2.12
	DK Score	-2.98-	1.65	-1.80
	Gameplay*DK	2.84**	0.75	3.80
	Total R^2	.055		
	Random Effects:		*SD*	
	Subject	110.9	10.53	
	Item	10.4	3.22	
Plays Ratings				
	Fixed Effects:			
	Intercept	63.33**	2.08	30.46
	Gameplay Type	1.71-	0.86	1.99
	DK Score	-2.67	2.03	-1.31
	Gameplay*DK	3.52**	0.73	4.79
	Total R^2	.053		
	Random Effects:		*SD*	
	Subject	183.154	13.53	
	Item	2.35	1.53	

**$p < .001$, *$p < .05$, -$p < .09$

Table 6.

Rating for each of the Four Dependent Variables. High and Low Domain Knowledge are Represented at +/- one Standard Deviation

Rating	**Domain Knowledge**	**Gameplay Type**	
		Structured	Unstructured
Structured			
	High	70.02	58.36
	Low	69.21	69.69
Unstructured			
	High	50.25	52.36
	Low	48.06	37.99
Strategic			
	High	67.80	58.39
	Low	68.32	68.10
Contained Plays			
	High	66.56	56.58
	Low	64.36	65.73

In all, results from Experiment 1 support the proposed hypothesis that domain knowledge affects the interpretation of structured gameplay. In the present, gameplay type affected one's perception of structure and one's amount of basketball knowledge moderated this effect. While findings were largely as expected, one somewhat surprising finding was related to the unstructured ratings. Participants with low domain knowledge tended to rate unstructured gameplay as more structured than structured gameplay, whereas high knowledge participants made little distinction based on unstructuredness (see Table 6). While this finding may at first appear anomalous, prior research on similarity judgments suggests that judgments of similarity and differences are not inverses (Medin, Goldstone, & Gentner, 1990; Tversky, 1977). The present work may be analogous. Thus, asking participants to rate how structured videos were appears to orient participant's attention to different features of the videos than asking participants to rate how unstructured the videos were. Here, high and low domain knowledge individuals treated these two ratings differently, however the current data does not yield insights as to the nature of the differences in how the ratings were made. This is a finding that warrants further investigation.

What do these results suggest regarding the central questions for Experiment 1? With respect to the Basketball Domain Knowledge Questionnaire, results suggest that this measure appears to be both reliable and valid. As predicted, the instrument had a high degree of internal consistency with an acceptable Cronbach's alpha (.78). In terms of the validity of the measure, we anticipated that participants with high and low knowledge, as measured by the instrument, would react differently to the manipulation of structure. This appears to be the case. As a participant's score on the Basketball Domain Knowledge Questionnaire increased, so did the positive effect of gameplay type (i.e., structuredness) on rating judgments. Thus, it appears that the questionnaire is able to differentiate high and low domain knowledge participants in a meaningful way.

A second purpose of Experiment 1 was to ensure that the manipulation of gameplay type in basketball videos (i.e., structuredness) was valid. If the manipulation of gameplay type is valid, it was anticipated that ratings of structured and unstructured videos should reflect this, especially among participants with a high degree of basketball knowledge. Results appear to confirm this prediction. Gameplay type significantly affected structured and unstructured ratings while having marginally significant affects on strategy and play ratings. Importantly, the effect gameplay type appeared to be dependent on the amount of domain knowledge a participant had.

Participants with a greater degree of basketball knowledge appeared be more sensitive to the manipulation of gameplay type.

Findings from Experiment 1 are in line with previous research on the role of prior knowledge in event comprehension (De Groot 1978; Chase & Simon, 1973; Laurent, Ward, Williams, & Ripoll, 2006; Ripoll, Baratgin, Laurent, Courrieu, & Ripoll, 2001) and lend support to the central claim of this thesis, wherein prior knowledge affects the understanding of events to the extent that they are structured. While domain knowledge appears to affect the comprehension of structure in events, it remains unclear whether domain knowledge affects segmentation processes or the updating processes that occur after event boundaries are perceived and the gating mechanism is “open”. The next chapter explores these issues, examining the effect of prior knowledge on event segmentation.

CHAPTER 4

EXPERIMENT 2

The goal of Experiment 2 was to explore the role of prior knowledge in the segmentation and interpretation of complex events. Findings from Experiment 1 suggest that people with differing levels of prior knowledge may understand events differently, at least at some level. In the present Experiment, the extent to which prior knowledge affects early encoding processes is explored. Using the piloted materials from Experiment 1, participants with a varying degree of basketball knowledge were asked to watch and segment basketball clips that were more or less structured in nature.

In accordance with theories of event cognition and results from previous research, the following two alternative hypotheses are proposed: the *Expertise Hypothesis* and the *Bottom-up Hypothesis*. According to the *Expertise Hypothesis*, schema activation will allow prior knowledge and expertise to guide attention and stabilize prediction. As a result, event processing will be influenced, such that both event segmentation and event interpretation will be affected. Thus, event knowledge will modulate the impact that perceptual features have on segmentation.

This hypothesis gives rise to several predictions. First, in accordance with this hypothesis, it is predicted that there will be greater agreement in segmentation among experts than novices for videos of structured gameplay. For unstructured gameplay, it is predicted that there will be no difference in segmentation agreement since expertise and the associated event schemas will be irrelevant. Thus, it was predicted that there will be a greater level of agreement within group (i.e., experts) than between groups (i.e., expert-novice) for structured, but not unstructured, gameplay. It was also predicted that segmentation frequency would differ between experts and novices for structured gameplay (i.e., differences in segmentation units), however, the directionality of this prediction is remains unclear based off prior research (see Herzmann & Curran, 2011; Zacks, 2004). Lastly, it is predicted that a greater level of knowledge will be manifest in expert's interpretations of structured game play than novices' interpretations.

According to a *Bottom-up Hypothesis,* segmentation will be gated from prior knowledge such that event processing will be largely bottom-up in nature. It is only during later processing that event schemas and event knowledge will take effect. From this hypothesis a main effect of gameplay type is predicted. Given that segmentation is known to be hierarchically structured (e.g., Zacks, 2004), more structured gameplay should lead to higher levels of segmentation agreement than less structured gameplay, regardless of one's level of expertise. Thus segmentation will be driven by prediction error that occurs in response to discontinuity in action. In regard to event interpretation, differences are predicted to be made manifest, wherein experts are expected to demonstrate a greater degree of knowledge for structured gameplay than novices.

Methods

Participants

In order to facilitate the recruitment process, the Basketball Domain Knowledge Questionnaire was administered to all Psychology 102 courses at Northern Illinois University as a part of a mass survey. The mass survey included a number of measures from faculty and students conducting research at the university and students who elected to participate received course research credit for their participation. A total of 529 participants completed the survey. Participants scoring in the upper and lower thirds (above 70%, and below 30%, respectively) of the Domain Knowledge Questionnaire were invited, via email, to complete a fellow-up study. While this population was targeted in order to obtain participants with especially high and low knowledge, any student enrolled in an introductory psychology course was allowed to sign up and participate, regardless of their Domain Knowledge score. Eighty-seven participants (61% male, mean age = 18.92) were recruited to participate in Experiment 2 and were awarded course credit for their participation. One participant was dropped for incompliance (i.e., texting throughout the experiment).

Design

A within-participants design was used with gameplay type (structured, unstructured) as the independent variable. Segmentation frequency and agreement served as dependent variables (see below). A linear mixed effect model was used in order to examine differences in the segmentation of structured and unstructured videos for participants with a varying degree of domain knowledge.

Materials

Basketball Domain Knowledge Questionnaire and Segmentation Videos

The Basketball Domain Knowledge Questionnaire used in Experiment 1 was used in Experiment 2. Reliability was calculated for the entire mass survey sample (*N* = 529) using Cronbach's alpha. The instrument had acceptable internal consistency (alpha = 0.73). The average domain knowledge score was 4.7 out of 10 (*SD* = 0.27). The piloted basketball clips (6 structured, 6 unstructured) from Experiment 1 were also used in Experiment 2.

Motivation Measure

In order to assess components of motivation and task engagement, an experience sampling methodology measure (ESM; see Csikszentmihalyi & Larson, 2014) was used as a situated measure. In the present, a portion of the ESM developed by Shernoff and colleagues (2016) was used. The 6-item questionnaire included questions about one's interest, effort, mood, and beliefs about performance on the task (e.g., "Did you feel successful at the activity?"). Participants were instructed to respond to each item on a 5-point Likert-scale (1 being "not at all" and 5 being "very much") while reflecting upon their experience with the experimental tasks (see Appendix B). In the present Experiment, this measure showed an acceptable level of inter-consistency (Cronbach's alpha = .79); however, at the present time, no other results will be presented regarding ESM data.

Procedure

Upon completing an informed consent form, participants were seated in individual rooms at desktop computers. Participants were then given verbal and written instruction. Participants were instructed to watch each basketball clip and to press the spacebar whenever they felt that one meaningful event had ended and another had begun. They were told that there was no right or wrong way to do the activity, but that each video should contain multiple events. All videos were played silently (without audio) and were presented on 23-inch computer screens using E-Prime software. Each participant viewed 12 video clips total (6 structured and 6 less structured), presented in a random order. A practice trial was given in order to familiarize participants with the procedure.

After all videos had been segmented, participants were instructed to watch each video again and to provide a detailed description of what they saw immediately after finishing each video. This portion of the experiment was done through Qualtrics and videos were again silent. A practice trial and an example description were provided; however, a football clip was used in order to avoid activating any specific prior knowledge pertaining to basketball. After providing a description of each video, participants completed the ESM and a brief demographic questionnaire. Any participants that had not completed the Basketball Domain Knowledge Questionnaire during mass testing were given the questionnaire at the end of the study (N = 9). All participants were then thanked, debriefed, and dismissed. The experiment lasted approximately 60 minutes.

Results and Discussion

Data Cleaning

All data from two participants were dropped from analyzes due to computer malfunction or incompliance with task instructions (i.e., no segmentation data for 11 of the 12 videos). A total of 85 participants remained in the sample. Due to computer malfunction, each item that was randomly presented first to participants was recorded with error and was, therefore, excluded from the analysis. An additional 21 individual items were dropped from analyzes due to computer malfunction or incompliance with task instruction. All items appeared to be missing randomly.

Segmentation Frequency

All segmentation data were first analyzed for differences in segmentation frequency. To assess segmentation frequency, a procedure used by Zacks and colleagues was used (Zacks, 2004; Zacks et al., 2006; Kurby & Zacks, 2011). First, the total number of segmentation judgments for each participant's segmentation of a given clip were added up. This represents the number of event boundaries identified. A measure of unit length (i.e., how big the units were) was then calculated by dividing the length of each clip by the total number of events identified. Means for segmentation frequency are found in Table 7. Unit length (which will be referred to as segmentation frequency from here on) was then used as the outcome variable of a linear mixed effects model. Gameplay type was coded as 0, 1 for unstructured and structured videos, respectively. Gameplay type was added as an independent variable at level-1 while Domain

Knowledge (DK) scores were added as an independent variable at level-2. Both Gameplay type and Domain Knowledge were entered as centered variables.

Table 7.
Means (and standard deviations) for number of event boundaries, unit length, and agreement.

Gameplay Type	Number of Event Boundaries	Unit Length	Agreement
Unstructured	8.25 (6.18)	13.67 s (12.15 s)	0.68 (0.19)
Structured	5.80 (4.85)	19.05 s (13.81 s)	0.66 (0.22)

All analyses were performed using the lme4 package (Bates, Maechler, Bolker, & Walker, 2014) in R (R Core Team, 2013). The mean domain knowledge score for the sample was 60% (*SD* = 0.28). To begin, a null model was fitted with segmentation frequency as the outcome variable and subject and item as random effects. Results from this analysis indicated that significant variance in the dependent variable was accounted for by subject but not item (Subject *ICC* = 0.46, *DEFF* = 6.07; Item *ICC* = 0.07, *DEFF* = 1.76). Given the design effect (DEFF greater than 2) and the hierarchical structure of the data, a multilevel design was appropriate (Nezlek, 2008). As in Experiment 1, gameplay type (unstructured = 0, structured = 1), domain knowledge scores, and the interaction term (GP type*DK score) were then added to the analysis as predictors.

Results indicated that gameplay type was a significant positive predictor of segmentation frequency (p = .004). That is, unstructured videos were segmented more frequently than structured videos, controlling for one's domain knowledge. Domain knowledge and the interaction between domain knowledge and gameplay type were both non-significant predictors of segmentation frequency in this sample (p = .86; p = .27, respectively)(see Table 8). As will be discussed, it appears that these results are partially consistent with the *Bottom-up Hypothesis* in that domain knowledge has no effect on segmentation frequency. One potential explanation for the greater frequency of segmentation judgments for unstructured plays relative to structured plays is that there were more possession changes and shot attempts in the unstructured videos than the structured videos. Prior research in the context of sports (i.e., soccer) showed that participants tended to segment around activity associated with the ball (e.g., passes, possession changes)(Huff, Papenmeier, & Zacks, 2012). It is plausible that the current finding reflects a similar result.

Table 8.
Model Estimates for the Final Linear Mixed Model Predicting Segmentation Frequency

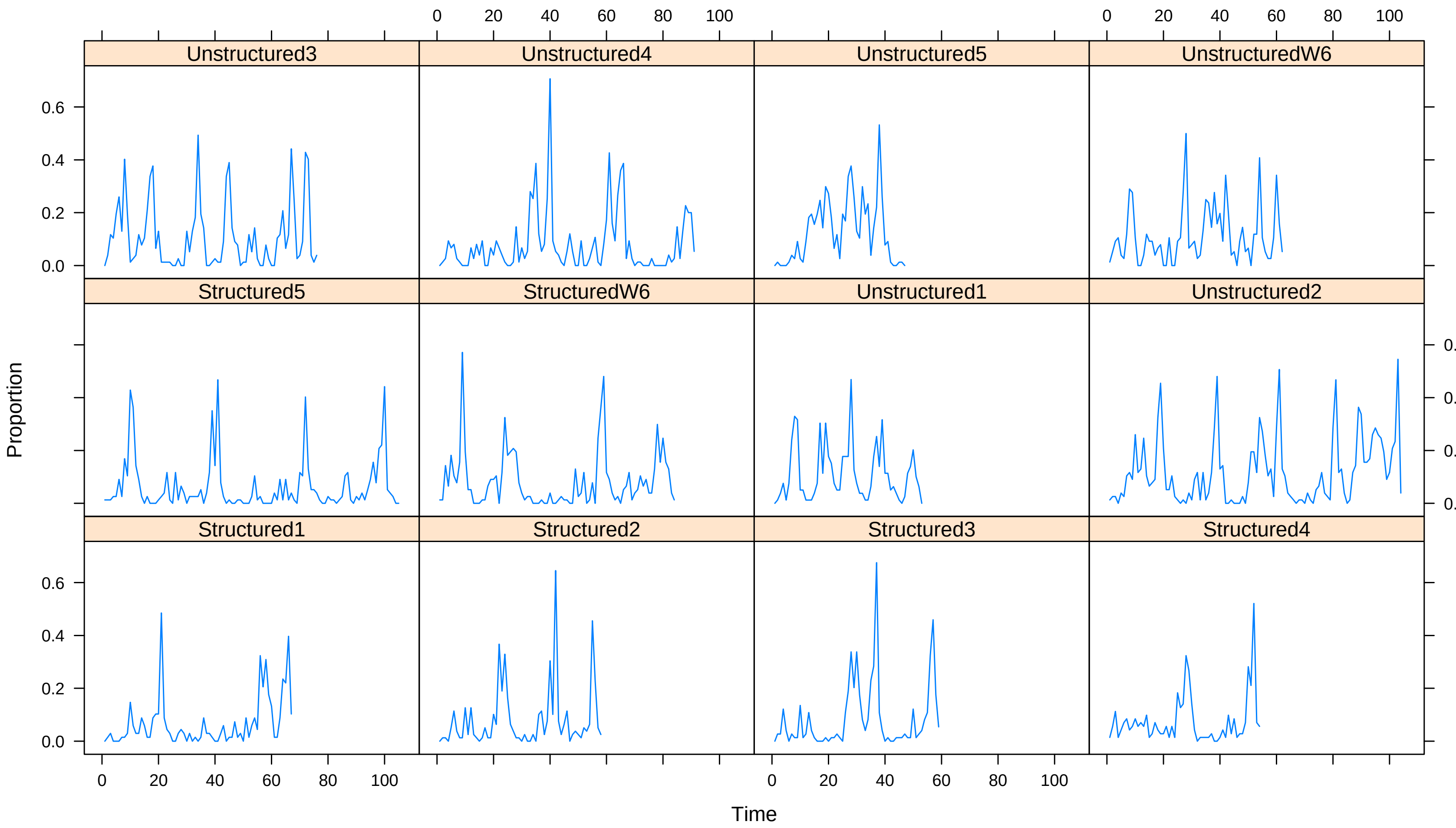
	Estimate	*SE*	*t*
Fixed Effects:			
Intercept	16.75**	1.25	13.38
Gameplay Type	-2.69*	0.74	-3.66
DK Score	0.18	1.06	0.17
GP Type*DK Score	0.33	0.30	1.10
Total R^2	0.061		
Random Effects:		*SD*	
Subject	86.25	9.29	
Item	5.44	2.33	

**p < .001, *p < .05

Segmentation Agreement

To assess segmentation agreement, each clip was divided into 1-second bins. It was then assessed whether or not a given participant made a segmentation judgment within each bin. As noted earlier, segmentation judgments are remarkably consistent both between participants and within participants over time (Speer et al., 2003). As such, a normative agreement for event boundary locations was derived by averaging together judgments from the entire sample (both experts and novices) for a given clip (see Figure 1 for a visual depiction). This norm was then used to determine how far each individual's (and each group's) judgments deviated from the given normal pattern. Following analyses used in previous research (Kurby & Zacks, 2011; Zacks et al., 2006), the point-biserial correlation between each individual's segmentation judgments and the segmentation probability for the group were calculated. Correlations were corrected to control for individual differences in the number of segmentation judgments following a procedure used by Kurby and Zacks (2011). Once correlations were calculated, they were converted into a normally distributed variable through Fischer's z transformation function. Converted correlations were then entered into a mixed effects model with structure as a repeated fixed factor and expertise as a between-subjects fixed factor (see Kurby & Zacks, 2011; Zacks et al., 2006 for review).

Figure 1.
Histograms Showing Normative Boundary Agreements for each Item



First, a null model predicting segmentation agreement, ranging from 0 to 1 (0 being no agreement, 1 being complete agreement), was fitted. This analysis revealed that significant variance in the dependent variable was accounted for by subject but not item (Subject *ICC* = 0.35, *DEFF* = 4.39; Item *ICC* = 0.01, *DEFF* = 1.09). Again, given the design effect (DEFF greater than 2) and the hierarchical structure of the data, a multilevel design was deemed appropriate (Nezlek, 2008). Next, gameplay type, domain knowledge scores, and the interaction term (GP type*DK score) were added to the analysis as predictors.

Results indicated that gameplay type, domain knowledge, and the interaction term were all non-significant predictors of segmentation agreement (p = .35; p = .45; p = .77, respectively)(see Table 9). As will be discussed in depth in the General Discussion, these results do not fully support either of the predicted hypotheses. Based on the *Bottom-up Hypothesis*, it was predicted that agreement would be higher for structured videos than unstructured videos, given that they should be more predictable in nature. In the present, structured and unstructured videos showed comparable agreement. Thus, results did not support this aspect of the predictions. In terms of domain knowledge, agreement was comparable between participants with high and low domain knowledge. Results will be furthered discussed in the General Discussion.

Table 9.

Model Estimates for the Final Linear Mixed Model Predicting Segmentation Agreement

	Estimate	*SE*	*t*
Fixed Effects:			
Intercept	0.63**	0.038	16.75
Gameplay Type	0.03	0.028	0.94
DK Score	0.04	0.056	0.76
GP Type*DK Score	-0.01	0.040	-0.29
Total R^2	.006		
Random Effects:		*SD*	
Subject	0.02	0.12	
Item	0.01	0.02	

**$p < .001$, *$p < .05$

Exploratory Analysis of Event Descriptions

In order to explore whether there were differences in the descriptions of videos of high and low domain knowledge participants an exploratory analysis was conducted. If people with high domain knowledge use their knowledge to interpret videos, more expert terms should be found in their event descriptions than in the descriptions of low domain knowledge individuals. Moreover, this effect should be more pronounced for structured videos containing multiple plays than for unstructured videos. In line with these hypotheses it was predicted that high domain knowledge individuals would use expert terms more frequently than low domain knowledge individuals. Additionally, it was predicted that an interaction would exist between gameplay type and expertise, wherein high domain knowledge participants would use expert terms more frequently for structured videos than unstructured videos.

To conduct the analysis, an upper and lower third of participants was selected from the sample. This resulted in 32 participants from the upper third (scoring 80% or higher on the domain knowledge questionnaire) and 33 participants from the lower third (scoring 40% or lower) for a total of 65 participants. All 12 protocols (6 structured, 6 unstructured) for each of the 65 participants were analyzed, resulting in a total of 780 protocols (approximately 73% of the dataset).

In order to conduct this analysis, a list of key terms was used. Key terms were selected from a list of common terms used by experts to describe subcomponents of plays and were the same terms used to identify materials in Experiment 1. Terms referred to both offensive and defensive plays. A total of six terms were used (see Table 1). For the analysis, a computer-based search in Excel was conducted for each of the key terms. Protocols containing at least one key term were marked with a 1 and protocols that did not contain any key term were marked with a 0, creating a binary dependent variable (see Table 10 for example descriptions from high and low knowledge participants).

Table 10.
Example descriptions from high and low knowledge participants. Highlighted words were key search items used in the analysis

High Knowledge Participant
"Weber St ran a set which included an off ball screen for the big man coming down the block. The ball was fed to him and they scored a layup. Murray st came down the court and ran an isolation play for their point guard. Weber st played very good defense not allowing him to drive. The ball was eventually kicked out to the wing which resulted in a Murray st 3 point make. The Weber st ran a pick and roll on the right wing which led to a baseline drive and a deflected pass out of bounds. They then ran a play to get the big man posted up and this led to an easy basket and including the foul."
Low Knowledge Participant
"The first team passed the ball around a lot during their possession and ended up missing their shot. the second team passed the ball around and found a wide open 3 pointer that made it. the first team then drove down the court, passed the ball which was tipped and went out of bounds. then the first team drove into the paint and got the layup with a shooting foul."

Mean likelihoods for mentioning key terms are presented in Table 11. A null model was fitted with participant and item as random factors and the likelihood of mentioning a key term at the item level as the outcome variable. This analysis revealed that a significant amount of variance was accounted for by participant (*ICC* = .42; *DEF* = 6.81) but not by item (*ICC* = .06; *DEF* = 1.89). Next, gameplay type (0 = unstructured, 1 = structured), domain knowledge (0 = lower third, 1 = upper third), and the interaction term (GP Type*DK Score) were added as predictors. Note that domain knowledge scores were added as a dichotomous variable rather than a continuous variable (as they were in previous analyses) due to the fact that only the upper and lower thirds of the data were analyzed in this experiment.

Table 11.
Mean Frequency and Standard Error (in parentheses) of Mentioning of Expert Terms

	Gameplay Type	
	Structured	Unstructured
High DK	0.26 (0.44)	0.18 (0.39)
Low DK	0.02 (0.14)	0.01 (0.07)

Results indicated that domain knowledge scores were a significant predictor of the likelihood of using expert terms ($p < .001$). Results suggest that participants with high domain knowledge (M = 0.22, SD = 0.41) had a higher likelihood of mentioning key terms than participants with low domain knowledge (M = 0.01, SD = 0.11). On the other hand, gameplay type and the interaction of gameplay type and domain knowledge were not significant predictors of the usage of expert terms (p = .26, p = .49, respectively). Thus, contrary to hypotheses, it appears that structured gameplay (M = 0.14, SD = 0.34) did not statistically elicit the use of more key terms than unstructured gameplay (M = 0.09, SD = 0.29). Final model estimates are shown in Table 12.

Table 12.

Model Estimates for the Final Linear Mixed Model Predicting the Likelihood of Using Expert Terms

	Estimate	*SE*	*z*
Fixed Effects:			
Intercept	-6.49**	1.16	-5.61
Gameplay Type	1.37	1.18	1.13
DK Score	4.48**	1.12	4.02
GP Type*DK Score	-0.81	1.18	-0.49
Total R^2	.123		
Random Effects:		*SD*	
Subject	2.20	1.48	
Item	0.46	0.68	

**p < .001, *p < .05

These are exploratory results and should be interpreted cautiously, however, they suggest that people with sufficient domain knowledge use their knowledge to interpret and understand complex events. Moreover, in conjunction with the results on segmentation agreement, these data suggest that these interpretative processes may happen during the updating that occurs after event boundaries are perceived. This is consistent with the gating assumption of EST. Specifically, EST postulates that prior knowledge becomes accessible only at event boundaries. Results will be discussed in greater detail in the General Discussion chapter.

CHAPTER 5

GENERAL DISCUSSION

A critical aspect of understanding complex events is recognizing the boundaries between the discrete actions that comprise them (Kurby & Zacks, 2008; Zacks et al., 2007; Zacks & Tversky, 2001). Event segmentation is a naturally occurring phenomenon that helps one understand dynamic events as they unfold over time (Speer et al., 2003; Zacks et al., 2006). While event segmentation is known to have important implications on learning and memory for events (Bailey et al., 2013; Ezzyat & Davachi, 2011; Kurby & Zacks, 2011; Sargent et al., 2013; Zacks et al., 2006), it remains unclear the extent to which prior knowledge plays a role in this process. Event Segmentation Theory (EST; Zacks et al., 2007) specifies that lower-level perceptual change leads to prediction error and the updating of event models (Kurby & Zacks, 2008). Specifically, EST assumes that event models are gated, such that prior knowledge exercises an effect primarily at event boundaries. Thus, segmentation is thought to be predominantly driven by perceptual change, in a bottom-up fashion, whereas, prior knowledge is thought to affect the updating that occurs at event boundaries rather than segmentation itself. A growing body of evidence supports these assumptions (e.g., Hard et al., 2006; Zacks et al., 2009), however, research investigating event segmentation in contexts where extensive background knowledge and expertise are likely to be activated are scarce. The goal of this thesis was to explore the extent to which domain knowledge affects the segmentation and interpretation of events in the context of highly dynamic, multi-agent situations that require the activation event schemata.

In the present study, two alternative hypotheses were proposed. The *Bottom-up Hypothesis* proposed that, in accordance with assumptions of EST, segmentation would be gated from prior knowledge such that prior knowledge would affect updating and the interpretation of events rather than event segmentation. Specifically, according to this hypothesis, there would be a main effect of event structure on segmentation such that videos of structured gameplay would have higher levels of segmentation agreement than videos of unstructured gameplay, given their predictability. Differences dependent on expertise would be manifest primarily during the interpretation of events. On the other hand, the *Expertise Hypothesis* proposed that domain knowledge would affect both the segmentation and interpretation of events given the right context. Thus, it was predicted that event segmentation and interpretation would vary depending on one's level of domain knowledge and that this effect would be specific to structured videos, but not unstructured videos. Moreover, similar to the *Bottom-Up Hypothesis*, the *Expertise Hypothesis* predicts differences in event interpretation to exist between experts and novices for structured but not unstructured videos.

In regard to segmentation, results from the present study did not fully support either of the proposed hypotheses. Results from Experiment 2 indicated that there were no significant differences in segmentation based on domain knowledge. That is, segmentation frequency and agreement were similar regardless of one's level of prior knowledge. This is consistent with the *Bottom-up Hypothesis* and suggests that segmentation appears to be gated from prior knowledge, as proposed by EST (Kurby & Zacks, 2008; Zacks et al., 2007). However, according to the

Bottom-up Hypothesis, it was predicted that there would be a main effect of gameplay type such that structured videos would have higher segmentation agreement than unstructured videos, given their predictability. This was not the case—both structured and unstructured videos showed similar levels of agreement. It may be that the prediction was not justified. It may be that segmentation judgments primarily are driven by changes in ball activity (Huff et al., 2012). Both structured and less structured plays obviously involve passes, shot attempts, made baskets, possession changes, etc. Given that shot attempts and possessions changes were more frequent in unstructured than structured videos (see Table 2), people may have consistently identified these locations as event boundaries. As a result, agreement for both structured and unstructured videos would be similar, despite differences in segmentation frequency, which was the case (see below). This means that while there were more frequent judgments in unstructured videos, people tended to make them at the same places.

In terms of segmentation frequency, there was a main effect of gameplay type such that unstructured videos were segmented significantly more often than structured videos. There are a few possible reasons for this. One possibility is that unstructured videos were more random and chaotic in nature, resulting in more frequent segmentation. Previous research suggests that activity is segmented more frequently when viewers cannot decipher an actor's goals or when the activity is more random than intentional (Wilder, 1978; Zacks, 2004, Experiment 1). Moreover, research suggests that unfamiliar content is segmented more frequently than familiar content (Graziano, Moore, & Collins, 1988), however, these types of effects on segmentation frequency have not been consistently reported (Hard et al., 2006; Zacks et al., 2001). Another possibility, as mentioned above, is that participants were more sensitive to shot attempts and possession changes (both of which were more frequent in unstructured videos than structured videos) than to other types of changes in gameplay. If this were the case, it would be expected that segmentation would be closely aligned with these types of changes in each video. Conducting a detailed content analysis, wherein specific features of the videos are mapped onto segmentation judgments, would help answer this question. For example, measuring how segmentation judgments correlate with components of plays (e.g., screens) and changes associated with the ball (shot attempts, possession changes) may provide insight into what was driving segmentation judgments for high and low domain knowledge participants. Content analyses similar to the one proposed here have been used in prior research (e.g., Hard et al., 2006; Magliano et al., 2012) and should be considered in future work.

What do results from the present study tell us about event segmentation and EST? Results from the present study are consistent with a growing body of research demonstrating that event segmentation is heavily influenced by lower-level perceptual change (Hard et al., 2006; Zacks, 2004; Zacks et al., 2001a; Zacks et al., 2009). When perceiving events, segmentation appears to be driven by sensory characteristics from the environment (e.g., movement features) rather than top-down knowledge structures (e.g., schemas). In the present study, prior knowledge was not shown to influence segmentation behavior—segmentation for participants with high and low knowledge was similar. Thus, results are largely consistent with assumptions of EST; event models appear to be gated, such that prior knowledge affects them primarily when event boundaries are perceived.

Above providing additional evidence for assumptions of EST, this work may have other important implications. Previous research has been largely limited to events with single actors performing relatively simple tasks (e.g., washing the dishes, watering plants). Moreover, most events used in prior research require minimal domain-specific background knowledge or expertise to understand. The present study extends the body of research on event segmentation in demonstrating that segmentation appears to be driven by lower-level perceptual change, even in complex, dynamic events where event schemas are likely to activated. Similar results were found when examining segmentation in soccer-fan viewers (Huff et al., 2017).

One interesting dimension of using sports videos to explore the present issue is that sports events are different than everyday events in regard to predictability. Everyday activities typically have transparent goal structures and clear intended outcomes. As a result, fine-grained event boundaries (e.g., moving from washing a one dish to the next) and course-grained event boundaries (e.g., moving from washing the dishes to drying them) are often aligned with the actor's overarching goals. In sporting events, on the other hand, the goal is often to be *un*predictable. Thus, while there are common components to all set plays, as described above, the idea is to surprise the opponent and catch them off-guard. Take, for example, a play called a "slip screen." Since pick and rolls are common in basketball, many teams run a "slip screen," wherein they fake like they're going to run a pick and roll but have the man that is about to set the screen dart toward the basket at the last minute. Given that players often don't anticipate this, it is likely that experts watching a film might not predict this either. They would, however, recognize this play after the fact. In this sense, the nature of the present study may not fully elucidate differences in predictability that could affect various aspects of event cognition. Thus, given the importance of predictability in EST, comparing current findings to findings from other studies examining everyday activities (e.g., Bailey et al., 2013; Sargent et al., 2013; Zacks et al., 2001a) is of interest.

The present research is also informative to the literature on sports expertise. Research in sports expertise suggests that experts are able to use knowledge to guide attention and make predictions about upcoming events (Abernethy, 1988; French & Thomas, 1987; Mann et al., 2007; McPherson, 2000; Starks, 1987). However, results from the present study suggest that segmentation—a process assumed to operate on prediction error—did not differ by domain knowledge. This discrepancy may be of interest. Clearly, experts show an enhanced ability to quickly and efficiently process domain-related stimuli (e.g., Mann et al., 2007; Williams, Davids, & Williams, 1999). One possibility is that this enhanced ability affects components of early processing (e.g., attentional mechanisms, eye movements) but not segmentation processes. There is some evidence to support this; experts exhibit different visual search behavior than novices (Mann et al., 2007; Savelsbergh, Williams, Van Der Kamp, & Ward, 2002; Stevens et al., 2010). The issue of prediction seems more perplexing. When considering this issue, it is important to keep in mind that predictive processes can occur at various levels. While EST stresses the role of lower-level prediction error in segmentation, prediction can also be made during later processing. For example, asking a participant to predict what happens next would likely necessitate the use of interpretive processes that occur after event boundaries have been established. Thus, it may be the case that prediction paradigms used in sports expertise experiments were tapping into a different level of prediction than those proposed to be used in segmentation processes. One final possibility is that differences in lower-level prediction and segmentation do exist but were not found in the present study due to the measure of expertise, the sample used, or the sensitivity of the segmentation task. These issues will be discussed in greater detail momentarily.

While prior knowledge appeared to have a minimal impact on segmentation, previous research suggests that it has significant impacts on comprehension processes (e.g., Bransford & Johnson, 1972; Long & Prat, 2002; Spilich et al., 1979; Voss et al., 1980). Results from the current study are consistent with this. In Experiment 1, results indicated an interaction between gameplay type and domain knowledge such that the effect of event structure on ratings was moderated by one's level of knowledge. Specifically, it appeared that participants with lower levels of domain knowledge were insensitive to gameplay type, rating both unstructured and structured videos similarly. These results parallel results from Allard et al. (1980) wherein basketball experts showed evidence of different perceptual and memory processes than novices, but only for structured basketball formations (see also Chase & Simon (1973)). Moreover, in the Exploratory Analysis, event descriptions from high and low domain knowledge participants differed in their use of expert terms. Experts were shown to use domain knowledge when interpreting and describing events. Event description tasks have been used in conjunction with segmentation tasks and have shown that descriptions reflect the same hierarchical partonomy shown in segmentation (Zacks et al., 2001). Moreover, consistent with the present study, prior research has shown that knowledge has a top-down effect on event interpretation processes (Hard et al., 2006; Zacks, 2004). Thus, the fact that participants with varying levels of domain knowledge appear to identify event boundaries similarly but render different event interpretations suggests that domain knowledge does affect event perception, but primarily at later stages of processing (Hard et al., 2006). The perception of event boundaries, driven by perceptual change, may help activate event schemas and thereby alter event interpretations (Hard et al., 2006; Zacks et al., 2001).

It is well established that expertise helps one identify important goal structures and how event episodes fit into goal structures (Bransford & Johnson, 1972; Long & Prat, 2002; Spilich et al., 1979; Voss et al., 1980). Furthermore, domain knowledge and an understanding of goal structure help facilitate recall and memory processes (Bransford & Johnson, 1972; Long & Prat, 2002; Spilich et al., 1979; Radvansky & Zacks, 2014; Voss et al., 1980). Results from the current study are consistent with these findings and suggest that event models appear to vary as a function of expertise. Prior knowledge serves to embellish event models at event boundaries. This is likely to occur during the updating process that is assumed to take place at event boundaries according to EST (Kurby & Zacks, 2007; 2012; Radvansky & Zacks, 2014; Zacks et al., 2007). In the present, the richness of event models was made manifest through interpretive processes and event descriptions—descriptions and ratings differed drastically depending on one's knowledge. It is presumably the depth and richness of event models that helps explain findings related to enhanced memory and encoding processes in other research (see Gold, Zacks, & Flores, 2017; Radvansky & Copeland, 2006; Radvansky et al., 2011; Schwan & Garsoffky, 2004).

Although results from the current study are consistent with previous literature in suggesting that segmentation is gated from knowledge (e.g., Hard et al., 2006; Zacks et al., 2009), results are far from definitive. There are a number of issues to consider before arriving at strong conclusions. One caveat to the interpretation of the current findings is the issue of grain-size. In the current study, there was a high degree of variability in the grain-size at which participants elected to segment videos (segmentation judgments ranged from 1 to 37). Zacks and colleagues often implore mechanisms to guide segmentation grain-size (e.g., Speer et al., 2003; Zacks et al., 2001a). For example, participants are often instructed to segment videos at a coarse or fine-grain (e.g., identifying the largest or smallest meaningful units, respectively). In other studies, feedback is given to participants on practice items in order to ensure that they are segmenting roughly at a desired unit length (J. Zacks, personal communication, March 8, 2018). In the present study, participants were given only general instruction, without specification of grain-size (e.g., press the spacebar whenever you feel that one meaningful event ends and another begins). This was done for two reasons. First, video clips were relatively short in length. As such, materials may not have afforded segmentation at multiple levels. Second, given that directing participant's attention toward specific features of events (e.g., specifying coarse vs. fine grain) is thought to diminish the role of top-down processes on segmentation (Hard et al., 2006; Huff et al., 2017), general instructions were used to maximize the potential effect of expertise on segmentation. While this approach was adopted here, there may be reasons to examine differences in grain-size in future work. For example, it is plausible that prior knowledge may have an affect on coarse-grained segmentation but not on fine-grained segmentation (Zacks, 2004). Manipulating grain-size in an expert-novice design may, therefore, be a fruitful future direction.

Another possible explanation for the null effect of expertise on segmentation may have to do with the segmentation task itself. It is plausible that there may have been a task demand that shifted participants toward perceptual change, rather than conceptual change, thereby masking the effect of prior knowledge. It is important to note that previous literature has shown that segmentation is a naturally occurring phenomenon. As noted earlier, Zacks and colleagues found that certain changes in brain activity were highly correlated with segmentation judgments, even when passively viewing films (Speer, Zacks, & Reynolds, 2007; Zacks et al., 2001b). Nonetheless, it may be that the task used made it difficult to explore the role of prior knowledge on early stages of event cognition. One alternative approach to a segmentation task is a prediction-based task, wherein participants are stopped periodically and asked to predict what will happen next. Prediction paradigms have been used previously with some success (Zacks et al., 2011), however, results in regard to expertise are somewhat mixed (see Eisenberg, Zacks, & Rodebaugh, 2017; Ericcson & Smith, 1991).

Another noteworthy issue is the use of domain knowledge as a measure of expertise. It is currently an open question as to how to best measure expertise. One way to measure expertise, as demonstrated in the current study, is through tests of domain knowledge (Long & Prat, 2002; Spilich et al., 1979; Voss et al., 1980). On the other hand, measures based on one's procedural knowledge are often used (Blasing, 2015; Laurent et al., 2006; see also Thomas & Thomas, 1994 for review of expertise measures). In the current study, a knowledge-based measure was used for a number of reasons. First, previous research has used subject interest and domain knowledge measures as measures of expertise in sports (e.g., Herzmann & Curran, 2011; Rawson & Van Overschelde, 2008). Moreover, in Experiment 1, participants that scored high on the domain knowledge measure rated structured and unstructured plays differently than participants that scored low on the measure. Thus, there appeared to be some evidence that the measure was valid. While a measure of domain knowledge was used here, perhaps a performance-based measure would have been more sensitive to differences in expertise. It is well documented that there is a strong relationship between the way in which information is encoded and the way in which it is later retrieved (e.g., Morris, Bransford, & Franks, 1977). As such, it could be that a performance-based measure of expertise would be more aligned with the segmentation task, given that both are in-the-moment processes. Related to this claim, some have suggested that it is the acquisition of skill that facilitates rapid encoding and enhanced memory processes in experts (Ericsson, 1996; Ericsson & Kintsch, 1995; Williams & Ericcson, 2005). Thus, measures based on one's experience or skill within a domain have also been used as measures of expertise, particularly in when examining expertise in sports (Blasing, 2015; Laurent et al., 2006; McPherson, 2000; see also Thomas & Thomas, 1994). In sum, it is possible that using a different measure of expertise or a population with a high level of expertise (e.g., college basketball players) may alter results.

Given the potential issues with task demands and measures of expertise mentioned above, it is worth discussing a few alternative ways of investigating the potential role of domain knowledge on early event encoding processes. The use of a prediction task, as mentioned previously, is one possibility. Another possibility is to implement a task wherein knowledge is built rather than measured. For example, Loschky, Larson, Magliano, and Smith (2015) used a jump-in-the-middle paradigm to investigate the role of top-down effects on segmentation. In their study, participants watched and segmented a film. Participants in one group were shown additional frames that contained important information relating to the story, while participants in another group were not. Results indicated that the participants that saw additional frames segmented the film differently than participants that did not. Similarly, an alternative course of action is to have participants segment videos of sports for which they have little to no knowledge (e.g., cricket, curling) and provide only half of the participants with information about the sport (e.g., goals, rules, etc.). This would allow one to compare the direct of effect of the learned material on segmentation in a novel sports context, rather than a sports context for which most participants have at least some knowledge, as was likely the case here with basketball. While only a few viable options are outlined here, the fact remains that future researchers should continue to explore the impact of prior knowledge on early event cognition using alternative tasks and nuanced approaches.

In conclusion, understanding the way in which people understand complex, dynamic events is at the center of cognitive psychology. Clearly, background knowledge shapes how events are processed and understood as they unfold over time. This study demonstrates that prior knowledge affects the understanding of events during later, rather than earlier, processing. Event segmentation was not affected by one's level of prior knowledge, however, ratings and interpretation of gameplay were. Moreover, this study adds to current research on event segmentation in that it specifies the role of prior knowledge in the context of complex, multi-agent events for which schemas are likely to be activated. As a part of event perception, event segmentation appears to be driven largely by perceptual change. Event knowledge, on the other hand, appears to affect updating processes that occur as event boundaries are perceived. The next time you're watching your favorite sports team in a tight game, remember that you're knowledge of the game will be hard at work helping you interpret and make sense of all the complexity of the intense event.

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APPENDIX A

Basketball Domain Knowledge Questionnaire

Please read each question below and select the best possible choice.

1. Which of the following is <u>not</u> the name of a basketball violation:
    a. Traveling
    b. Lane Violation
    c. Technical Foul
    d. Pass Interference
    e. Charging

2. 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

3. 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

4. How far from the basket is the free-throw line?
    a. 10 feet
    b. 15 feet
    c. 20 feet
    d. 25 feet

5. How long is the shot-clock in the NBA?
    a. 12 seconds
    b. 20 seconds
    c. 24 seconds
    d. 35 seconds

6. When can the inbound passer run along the baseline to help get the ball inbound?

a. Only after the opposing team scores
b. Only in the 4th quarter
c. Only when being defended
d. Anytime

7. 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

8. When an offensive player screens a defensive player, the defensive player might:
    a. Switch the man he/she is guarding
    b. Be called for a foul, depending on the situation
    c. Run toward the basket to prevent the offender from going there
    d. None of the above

9. 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 hoop to help rebound
    d. Either a or b are correct

10. After a player sets a screen or pick, he/she should:
    a. Roll to the basket with the front part of his/her body facing the teammate with the ball
    b. Roll to the basket with the back part of his/her body facing the teammate with the ball
    c. Make sure he sticks his knee out so he blocks the defensive player
    d. None of the above

11. What is the highest level of competition you've played basketball at?
    a. I've never played competitively
    b. Rec Leagues
    c. High School
    d. College or Professionally

APPENDIX B

Record of Experience (ESM)

Please answer the following questions all in regard to your experience completing the experimental tasks.

During the previous activity, …

	Not at all	A little	Somewhat	Pretty much	Very much
Were you enjoying what you were doing?	O	O	O	O	O
Did you feel good about yourself?	O	O	O	O	O
How well were you concentrating?	O	O	O	O	O
Did you feel successful at the activity?	O	O	O	O	O
Were you working hard at the activity you were doing?	O	O	O	O	O
Did you wish you were doing something else?	O	O	O	O	O