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The effects of domain knowledge and event structure on event processing

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Abstract
Research suggests that domain knowledge facilitates memory for domain-specific information through two mechanisms: differentiation, which involves the ability to identify meaningful, fine-grained details within a sequence, and unitization, which involves binding individual components from a sequence into functional wholes. This study investigated the extent to which individuals engaged in differentiation and unitization when parsing continuous events into discrete, meaningful units (i.e., event segmentation) and recalling them. Participants watched and segmented basketball videos. They then rewatched the videos and provided descriptions afterward. Videos were coded for the presence of higher order goals (A2 actions) and the individual sub-actions that comprised them (A1 actions). Results suggested that event segmentation behavior for participants with less knowledge was more aligned with changes in basic actions (A1 actions) than for participants with greater knowledge. When describing events, participants with greater knowledge were more likely than participants with less knowledge to use statements that reflected unitization.

Keywords Domain knowledge · Event segmentation · Goal hierarchies · Event memory

Sporting events are highly structured activities for which event knowledge often varies largely across individuals. To illustrate, imagine watching a basketball game on TV with a friend. The game consists of a series of events that can be broken into various sub-events at different levels (e.g., halves, quarters, possessions, plays). Suppose your friend knows a considerable amount about basketball, such as the rules, typical plays/maneuvers, and strategies, whereas you know very little. How might this difference in knowledge affect how the game is perceived and understood? Is your friend better able to group or organize the individual actions or sequences of the game into meaningful units? Are they better able to pick up on details that you may overlook? The questions that arise from this example illustrate the utility of studying event cognition and prior knowledge in the context of sporting events. As such, the present study explores how complex events are understood and the role of domain knowledge in this process.

In sports, knowing when and where to look is an essential aspect of successful performance (Mann et al., 2007). As such, it has been proposed that experts use their knowledge to direct their attention, which facilitates encoding processes by ensuring that the most meaningful information is extracted as efficiently as possible (Herzmann & Curran, 2011; Mann et al., 2007; Rawson & Van Overschelde, 2008; Williams et al., 1999). Experts tend to have fewer eye fixations of longer duration than novices (Mann et al., 2007), are faster and more accurate at picking up perceptual cues (for basketball references see Laurent et al., 2006; Ripoll et al., 2001), and are able to rapidly anticipate and predict upcoming actions (Abreu et al., 2012; Araujo et al., 2006).

Two mechanisms have been proposed to account for differences in perceptual processing based on domain knowledge: unitization and differentiation (Goldstone, 1998; Herzmann & Curran, 2011). Unitization involves the ability to merge individual components into functional wholes (Herzmann & Curran, 2011). This may be seen as

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a type of holistic processing wherein a sequence is seen in its entirety, rather than in pieces (Bukach et al., 2006; Herzmann & Curran, 2011). For example, it is possible in the hypothetical example that your friend is able to understand how the complex, dynamically changing actions of the players are organized into distinct plays. On the other hand, you are less able to organize the players' behaviors in a goal-structure because you lack an understanding of the typical plays used in basketball.

In contrast, differentiation involves the separation of bound percepts from one another (Herzmann & Curran, 2011). This involves the ability to identify meaningful, fine-grained details within a sequence and is associated with superior within-category discrimination. To illustrate these two processes, consider again the example from the beginning of this paper. Your friend, who has high basketball knowledge, may be able to identify large sequences of set plays (e.g., "they ran a pick-and-roll on the block as part of a larger play and got a good shot"; better unitization), where a low knowledge viewer might see only the individual actions (e.g., "a player ran down the court and passed the ball to a teammate who shot it"). Alternatively, your knowledgeable friend may pick up on details that a low knowledge viewer might have missed, recognizing important individual components of a play (e.g., "the point guard made a good pass to a teammate who was wide open thanks to a screen that was set"; better differentiation). Importantly, when individuals use their knowledge to identify meaningful breaking points in events (i.e., segment activity) there may be differences in the locations they identify and these differences may be related to underlying goal-structures (Kurby & Zacks, 2019; Levine et al., 2017).

In terms of event memory, it is well known that people with a high degree of domain knowledge have superior memory for domain-related information (see Ericsson et al., 2006; Gobet, 2015). One approach to examine this effect is to manipulate the structure of domain-specific events such that features of the events are more or less aligned with an individual's event schemata (e.g., classic chess formations vs. random placement; Chase & Simon, 1973; De Groot, 1978). Results from these studies suggest that high knowledge individuals possess a distinct advantage in memory for structured rather than unstructured stimuli; however, high knowledge individuals appear to outperform low knowledge individuals even with unstructured stimuli (see Gobet & Simon, 1996). This suggests that experts not only use high-level structures, such as schemata, to process broad-level goal structures, but that they are also able to use small-level structures, akin to chunks, to facilitate memory for smaller units of information that occur in unstructured formations by chance (Sala & Gobet, 2017). The extent to which people with high domain knowledge draw upon memory related to differentiation and unitization at the time of recall requires further examination.

We explored these issues in the context of event segmentation (Kurby & Zacks, 2008; Zacks, 2020), which is the process of chunking continuous spatiotemporal information into discrete, meaningful units during encoding (Kurby & Zacks, 2008; Zacks, 2020). Substantial evidence suggests that people habitually segment events and that memory for events is organized around this perceived structure (e.g., Newtson, 1973; Radvansky & Zacks, 2011; Zacks et al., 2006). Event segmentation has strong ties to learning, memory, and action execution (Bailey et al., 2013; Flores et al., 2017; Newberry & Bailey, 2019; Sargent et al., 2013) and appears to be a basic, independent aspect of event memory, uniquely predicting memory in both younger and older adults alike (Sargent et al., 2013).

Segmentation is important, in part, because it affords the perception of how actions are related to the goals and subgoals that make up human behavior. Research suggests that viewers segment activities based on how they perceive their underlying goal structure (Kurby & Zacks, 2019; Levine et al., 2017). In one study, Kurby and Zacks (2019) had participants watch short movies of everyday activities and segment them into events, while concurrently describing what was happening in the videos. To examine the relation between segmentation and goal structure, activities in the videos were coded using a goal-based classification system, the Action Coding System (Schwartz et al., 1991). Basic actions that corresponded to the smallest components of a goal (i.e., actions that produced a single transformation of an object, such as picking up a plate) were identified (A1 units), along with how these actions combined to form larger goal units (A2 units; doing the dishes). This coding afforded the identification of the underlying goal structure of the activities in the movies. Results suggested that segmentation judgments were related to changes in these goals and subgoals; viewers were more likely to perceive an event boundary when there were changes in the goal structure of an activity. Additionally, participants described the activities using A1 and A2 unit information. This suggests that segmentation processes are sensitive to the goal-structure of activities and that information about goals is used to encode information into event models.

According to theories of event cognition, people utilize both perceptual and conceptual information when constructing event models (Radvansky & Zacks, 2014; Zacks, 2020). That is, segmentation is thought to be affected by objective features of the ongoing situation (e.g., changes in visual motion, body position) in a bottom-up fashion, as well as by one's knowledge of the ongoing situation (e.g., prior knowledge, schemas) in a top-down fashion (Zacks, 2004; Zacks et al., 2009). While there is strong support for the influence of perceptual cues on segmentation behavior (e.g., Hard et al., 2006; Zacks et al., 2001; Zacks et al., 2009), evidence supporting the role of knowledge is somewhat mixed. Individuals appear to be able to sufficiently extract event-related meaning from perceptual information, even when they have minimal prior knowledge (e.g., Hard et al., 2006; Zacks et al., 2001; Zacks et al., 2009). Conversely, a growing body of research suggests that event segmentation may be influenced by prior knowledge, wherein prior knowledge (general knowledge or one's mental model for the event) has been shown to be associated with segmentation behavior when manipulating context, perspective, and familiarity (Loschky et al., 2015; McGatlin et al., 2018; Newberry & Bailey, 2019). Importantly, a substantial portion of the research that shows a weak association between prior knowledge and segmentation (i.e., that people rely on perceptual change, regardless of their knowledge) has been limited to simple dot animations (e.g., Hard et al., 2006; Zacks, 2004) and/or events with single actors performing relatively simple tasks (e.g., washing the dishes, watering plants; e.g., Zacks et al., 2009). The hierarchical structure of sporting events may provide an opportunity for domain knowledge to affect segmentation. That is, people with greater knowledge may be able to use that knowledge to recognize the extent that players are executing plays or distinct actions that comprise the plays and may perceive boundaries based on that recognition. Additionally, the involvement of multiple agents (i.e., players) as well as a lower predictability of reaching the goals may contribute to the higher complexity of sporting events compared to simple, routine everyday activities.

There are a few studies that have explored the role of prior knowledge in segmentation in domains that involve complex, dynamically changing behaviors in which there are clear experts and novices. Bläsing (2015) found that expert dancers segmented a choreographed phrase less often than novice dancers. As novices increased their familiarity with the phrase, however, their segmentation became less frequent and more similar to that of experts. Similarly, in the context of figure-skating, Levine et al. (2017) found that experts identified similar event boundaries to one another and that these boundaries were based around inherent goal-structures. In contrast, event boundaries identified by novices were less aligned with these goal-structures. The results of these studies are consistent with the notion that prior knowledge of complex dynamic activities affords unitization.

Of particular interest to the present study, Newberry et al. (2021) assessed the extent to which differences in prior knowledge were related to the segmentation of basketball clips[1]. Researchers had participants segment structured gameplay and assessed the extent to which segmentation frequency and agreement varied by domain knowledge. When considering the smallest meaningful units, results indicated that participants with greater knowledge segmented more frequently than participants with less knowledge. When considering larger meaningful units, participants with greater knowledge tended to agree more on event boundaries than people with less knowledge. While this study did not directly test hypotheses related to differentiation and unitization, results suggest that changes in domain knowledge were related to changes in segmentation and that high knowledge individuals engaged in segmentation differently, depending on the task.

However, not all studies using a segmentation task in these contexts have yielded clear differences in how experts and novices understand the event structures of the events. Research involving soccer suggests that participants tended to segment around activity associated with the ball (e.g., passes, possession changes; Huff et al., 2012; see also Antony et al., 2021) and that this process is unbiased by fandom (i.e., one's orientation toward one team or another; Huff et al., 2017). It may be the case that activities that involve a salient object are segmented primarily on changes in that object, albeit the results of Newberry et al. (2021) do not support this possibility.

The current study

In the present study, we were interested in whether people would naturally engage in differentiation or unitization when no explicit processing goal was provided (e.g., natural viewing). Participants completed a domain knowledge questionnaire and watched and segmented previously piloted basketball video clips. Afterward, participants rewatched the videos and provided written descriptions of what they had seen in as much detail as possible. Videos were coded with the Action Coding System (ACS; Schwartz et al., 1991) for the presence of higher-order goals (A2 actions) and the individual sub-actions that comprise them (A1 actions; see also Kurby & Zacks, 2019). This coding allowed us to examine the relation between segmentation, domain knowledge, and higher and lower-level actions.

There were at least two possibilities regarding the influence of knowledge on segmentation of the video clips. One possibility was that people would rely entirely on perceptual change and basic action changes (A1s and A2s) to segment activity and that knowledge would have a minimal effect on segmentation (e.g., Hard et al., 2006; Zacks et al., 2009). If this were the case, segmentation judgments would be related to basic action changes but unrelated to variability in domain knowledge scores. Another possibility was that segmentation would be associated with domain knowledge, such that

[1] This study was conducted at the same time as ours at a different institution with some overlap in materials and methodology.

people with higher knowledge encoded information differently than people with lower knowledge (e.g., Bläsing, 2015; Levine et al., 2017). In this case, individuals with high domain knowledge might have engaged in unitization or differentiation when segmenting ongoing activity.

According to a unitization hypothesis, people with greater domain knowledge should be less attentive to individual actions (A1s) than people with less domain knowledge and should be more likely to segment on units of change that are meaningful at a higher level (A2s). Thus, according to this hypothesis, domain knowledge should interact with *A1 actions* in predicting segmentation such that as prior knowledge increases, the association between event segmentation and A1 completions decreases. On the other hand, as prior knowledge increases, the likelihood should increase at A2 actions.

Conversely, according to a differentiation hypothesis, people with greater knowledge should be more attentive to individual actions and elements that make up gameplay (A1s) than people with less knowledge. Thus, according to this hypothesis, domain knowledge should interact with *A1 actions* in predicting segmentation, such that the association between event segmentation and A1 completions should increase as domain knowledge increases.

Importantly, both of these hypotheses accommodate the presence of a three-way interaction, wherein unitization and/or differentiation are more pronounced for structured than unstructured gameplay. That is, people with higher knowledge may be more attentive to changes in A2 (unitization) or A1 (differentiation) actions when watching structured gameplay than unstructured gameplay. Thus, there would be a Knowledge × Gameplay Type × A2 (or A1) interaction, such that the interaction between knowledge and A2 (or A1) actions should be greater for structured videos than unstructured videos.

With respect to the event memory, we examined the event descriptions that participants produced after rewatching each video and coded them for (1) the presence of domain-specific vocabulary terms and (2) the extent that they contained statements reflecting unitization and differentiation. The assessment of the use of domain-specific basketball terms was done to validate that increases in prior knowledge scores were related to the use of that knowledge to recall the events in the videos. Given that people with higher domain knowledge have an advantage for domain-specific information in general and a distinct advantage for structured stimuli, we hypothesized that participants with higher domain knowledge would use more expert/domain-specific vocabulary terms, especially when describing structured videos.

The consequences of using differentiation and unitization at the time of encoding may be associated with the subsequent recall of event-related information; however, this issue requires further exploration. As such, we used participants' event descriptions to assess the extent to which participants engaged in differentiation and unitization when recalling the videos. According to the unitization hypothesis, as prior knowledge scores increase, so should the presence of statements reflecting unitization in event descriptions. This main effect could be qualified by an interaction with gameplay such that this difference is more strongly reflected in the structured videos because they are likely to be perceived with more hierarchical structure. According to the differentiation hypothesis, as prior knowledge scores increase, so should the presence of statements reflecting differentiation in event descriptions. This main effect could be qualified by an interaction such that this effect is more strongly manifested in the unstructured videos because they are likely to be perceived with less hierarchical structure. In addition to testing these hypotheses, we assessed the extent to which domain knowledge, event structure, and segmentation related to the use of statements reflecting differentiation and unitization at recall. This was motivated by prior research suggesting that segmentation agreement may be predictive of event memory (Bailey et al., 2013; Flores et al., 2017; Zacks et al., 2006).

Methods

Participants

The Basketball Domain Knowledge Questionnaire (see below) was administered as part of a mass testing survey given to students enrolled in introductory psychology courses at the large, Midwestern university where data was collected. A total of 529 participants completed the survey. Participants who scored above 70% or below 30% on the Basketball Domain Knowledge Questionnaire were invited, via email, to participate in the study; however, any student enrolled in a psychology course was permitted to participate. Eighty-seven participants (61% male, M_{age} = 18.92 years) with a broad range of knowledge scores (0%–100%) participated in the study. Participants were awarded course credit for their participation.

The sample size for this study was based on an a priori power analysis conducted using G*Power (Faul & Erdfelder, 1992) in which we estimated that approximately 88 participants would be needed for a small to medium (d = .24; Magliano et al., 2012) effect size. However, it is important to note that when the study was originally conceived, the intent was to treat domain knowledge as a dichotomous variable based on a median split in a 2 (expert vs. novice) × 2 (structured vs. unstructured play) analysis of variance (ANOVA). The decision to treat domain knowledge as a continuous variable with mixed-effects modeling (see Design section) was made after data collection was completed and was done to increase power and to avoid negative consequences associated with dichotomizing continuous variables (e.g., McClelland et al., 2015).

Materials

Basketball Domain Knowledge Questionnaire

An adapted version of a questionnaire developed by French and Thomas (1987) was used in the current study. This scale was previously shown to be reliable (alpha = .86) in an adolescent population and was adapted in similar research with adults (Newberry et al., 2021). Here, a small subset of items was adapted and used. The questionnaire consisted of 10 multiple-choice items with questions addressing terminology, strategy, and general principles of the game (e.g., "Which of the following is not a violation in basketball . . . " "After a player sets a screen, he/she should . . ."; the questionnaire can be found at: https://osf.io/pgfvk/).

We piloted the Basketball Domain Knowledge Questionnaire in a separate experiment and found it to be both reliable and valid (see section below). In the present study, reliability for the entire mass survey sample (N = 529) was found to be acceptable (Cronbach's alpha = 0.73). Domain knowledge scores ranged from 0% to 100% with an average of 60% (SD = 28%) for the sample.

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. Generally speaking, structured gameplay contained long stretches of organized play, wherein multiple set plays were being attempted or executed (e.g., pick and rolls), while less structured gameplay consisted of mostly unorganized play that was more improvised in nature (e.g., back and forth, improvised ["run-and-gun"] gameplay, fast-breaks). There were 12 videos total (6 structured, 6 unstructured). Average video length was equated across video types. Video clips ranged from approximately 60 to 175 seconds with a mean length of 70.67 seconds (SD = 20.07). Only videos with minimal editing were selected. All games were filmed from a high vantage point with a mounted, wide angle that required no zooming. Example materials can be found online (https://osf.io/pgfvk/). Additional detail on the selection and piloting of materials can be found online (https://osf.io/uhxcb/).

As mentioned above, we ran a pilot study to validate the use the Basketball Domain Knowledge Questionnaire as well as the selected videos. In this study, participants were asked to watch the video clips and rate the extent to which gameplay was structured, strategic, and contained organized plays. Results suggested that participants with higher scores on the Basketball Domain Knowledge Questionnaire were more sensitive to the manipulation of gameplay type. This suggests that the manipulation of gameplay type was valid and that the questionnaire was able to differentiate high and low domain knowledge participants in a meaningful way (see https://osf.io/uhxcb/ for more detail).

Videos and action coding system

The Action Coding System (Schwartz et al., 1991) was used to identify higher-order goals (A2 actions) as well as the individual sub-actions that comprised them (A1 actions) for all 12 videos. Given that the goal in basketball is to score by getting the ball in the hoop during your possession (or, in the case of defense, to prevent the opposing team from scoring during a possession), we defined A2 actions in terms of possession changes (e.g., made baskets, missed baskets, steals, turnovers, breaks in gameplay [ball out of bounds]). A1 actions were defined as any number of actions that players engaged in to score baskets (i.e., to complete A2 actions). These included passing the ball, catching the ball, setting screens, shooting, rebounding, and so on. Videos were played using QuickTime media player and actions were identified. The time at which the completion of each action occurred was recorded in milliseconds along with the type of action (A1 or A2). The mean number of A1 actions for structured and unstructured videos was 48.8 (SD = 11.13) and 50.7 (SD = 14.92), respectively. The mean number of A2 actions for structured and unstructured videos was 3.2 (SD = 0.75) and 5.5 (SD = 1.38), respectively.

Design

A within-participants design was used with gameplay type (structured, unstructured) and goal structure (A1, A2 actions) as the independent variables. Domain knowledge served as a between-participants variable and was treated as continuous in all analyses.

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" (Newtson & Engquist, 1976). They were told that there was no right or wrong way to do the activity, but that each video would contain multiple events. All videos were presented on 23-in. computer screens using E-Prime software. Videos were played silently (without audio) to allow participants to activate their own knowledge when segmenting and describing

Table 1 Example descriptions from high- and low-knowledge participants

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 *post*ed 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."

The italicized words were key search items used in the analysis

videos, rather than relying on information provided by the commentators/broadcasters. Each participant viewed 12 video clips total (6 structured and 6 less structured), presented in a random order. As mentioned, all videos had been previously piloted. Participants were provided a practice trial wherein they segmented one short basketball clip in order to familiarize themselves with the procedure.

After all videos had been segmented, participants were told 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 to avoid activating any specific prior knowledge pertaining to basketball. After providing a description of each video, participants completed 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 ($N = 10$).[2] All participants were then thanked, debriefed, and dismissed. The experiment lasted approximately 60 minutes.

Protocol analysis

To evaluate whether participants with high domain knowledge used their knowledge when describing gameplay, event descriptions were assessed for the use of key terms commonly used by experts in describing gameplay. The following eight key terms were used: *screen* (or *pick)*, *roll*, *post-up*, *cut*, *set*, *play*, *zone*, *switch*, *double-team*, *mismatch*. These terms were selected from a list of key terms online and were the same terms used to identify materials in the pilot study (with the addition of the words "set" and "play"; see https://osf.io/uhxcb/ for more detail). For the analysis, a computer-based search in Excel was conducted for each of the key terms. The number of terms was then counted for each protocol, creating a continuous dependent variable (see Table 1 for example descriptions from high and low knowledge participants).

To assess our primary hypotheses with respect to event memory, event descriptions were coded categorically from 0 to 3 based on the number of statements reflecting differentiation and unitization (see Table 2). Statements that reflected specific actions or outcomes of actions were coded as differentiation (e.g., "he made a basket"; "the ball went out of bounds"; "she shot the ball"; "he passed the ball"), whereas statements that reflected the grouping of actions or subactions were coded as unitizations (e.g., "they ran a play"; "they ran pick and roll"; "there was a fast break"). Actions described at a global level were considered unitizations and were often expressed as macro-propositions (e.g., "Weber State had a bad possession"). Interrater reliability for differentiation and unitization scores were calculated separately on a subset of 10% of the data ($n = 103$ protocols) and was found to be acceptable (weighted Cohen's kappa of .94 and .75, respectively). The complete codebook can be found online (https://osf.io/pgfvk/).

Results

Overview of analyses

Data analyses are presented in three sections. In the preliminary analyses section, analyses related to segmentation agreement are reported. We also report results from the key term analysis that was intended to verify that participants

Table 2 Coding rubric for differentiation and unitization scores

Code	Differentiation Description	Unitization Description
0	No specific actions	No unitizations
1	1–2 specific actions	1–2 unitizations
2	3–4 specific actions	3–4 unitizations
3	5+ specific actions	5+ unitizations

[2] Primary analyses were run with and without these 10 participants and the pattern of results remained the same.

use their prior knowledge when recalling. In the second section, we report analyses associated with testing our hypotheses in the context of the event segmentation task and in the third section, we report analyses associated with testing our hypotheses in the context of the event description task.

Data cleaning

All data from three participants were dropped from analyses due to computer malfunction or noncompliance with task instructions (i.e., no segmentation data for 11 of the 12 videos; texting throughout experiment). A total of 84 participants remained in the sample. Due to computer malfunction, each item (i.e., video) that was randomly presented first to participants was recorded with error and was, therefore, excluded from analyses. An additional 21 individual items were dropped from analyses due to computer malfunction or noncompliance with task instruction.

Preliminary analyses

Segmentation agreement

Segmentation agreement is a measure intended to assess the extent to which an individual's segmentation agrees with the group norm (Zacks et al., 2006). Importantly, while the analysis regarding segmentation agreement was intended to determine how closely people segment to the norm, analyses involving the content analysis were designed to determine the extent to which individuals attended to different features of the stimuli. It is the latter analyses that pertain to the primary hypotheses specified in the introduction.

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. 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, by bin. This norm was then used to compute the correlation between each person's segmentation pattern and the group as a whole. 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).

Descriptive statistics for segmentation agreement are presented in Table 3. A linear mixed-effects model was conducted to assess the extent to which segmentation agreement varied as a function of knowledge and gameplay type. Gameplay type, domain knowledge, and the interaction term (Gameplay Type ×Domain Knowledge) served as predictors and segmentation agreement as the outcome variable. Participant and item were entered as random effects. Results from the model are summarized in Table 4. Gameplay type, domain knowledge, and the interaction term were all non-significant predictors of agreement.

Key term analysis

The mean likelihood of mentioning a key term was 0.27 and ranged from 0 to 10 terms per protocol. Means by group are presented in Table 5. A linear mixed-effects model was conducted with frequency of mentioning key terms as the dependent variable and domain knowledge (as a continuous variable), gameplay type, and the interaction term (DK × Gameplay Type) as independent variables. Participant and item were entered as random effects.

Results from the model are summarized in Table 6. We hypothesized that increased prior knowledge would be related to the use of key terms at the time of recall. Results revealed that domain knowledge was a significant predictor of the use of key terms, such that participants with higher domain knowledge tended to produce more key terms when describing videos. Moreover, the interaction between domain knowledge and gameplay type was a significant positive predictor, such that participants with higher domain knowledge tended to use more key terms when describing structured videos than unstructured videos. This result is consistent with our hypotheses and serves to further validate that increases in prior knowledge were related to the use of that knowledge when recalling event-related information. However, it is important to note that there is a low frequency of key terms used in the gameplay descriptions, which tempers the strength of the conclusions that can be drawn from these analyses.

Primary analyses

Hypothesis testing: Segmentation task analyses

To examine the extent to which domain knowledge and event structure were associated with segmentation behavior, a

Table 3 Means (*SD*) for segmentation agreement by gameplay type and domain knowledge (DK)

DK	Gameplay Type	
	Structured	Unstructured
High ($n = 43$)	0.66 (.22)	0.69 (.20)
Low ($n = 41$)	0.64 (.22)	0.66 (.19)

DK was included as a continuous variable in analyses but is represented here using a median split

Table 4 Model estimates for the final linear mixed model predicting segmentation agreement

	Estimate	*SE*	*t*	*p* value
Fixed Effects:				
Intercept	0.65**	0.04	17.87	<.001
Gameplay Type	−0.03	0.02	−1.17	.25
DK Score	0.03	0.05	0.59	.55
GP Type × DK Score	0.01	0.03	0.41	.68
Random Effects:		*SD*		
Subject	0.02	0.13		
Item	0.01	0.02		

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

Table 6 Model estimates for linear mixed model predicting the likelihood of using key terms

	Estimate	*SE*	*t* value	*p* value
Fixed Effects:				
Intercept	−0.10	0.12	−0.82	
Gameplay Type	−0.10	0.09	−1.04	.30
DK Score	0.47*	0.18	2.58	.01
GP Type × DK Score	0.48**	0.13	3.74	<.001
Random Effects:		*SD*		
Subject	0.18	0.42		
Item	0.01	0.08		

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

logistic multilevel model was constructed with segmentation judgments as the dependent variable. We coded each 1s bin for whether there was a completion of an A1 unit or an A2 unit, which were then entered as predictors. Additionally, gameplay type (unstructured = 0, structured = 1), domain knowledge scores (continuous), A1, and A2 actions were entered as predictors, along with all interaction terms. A measure of moment-to-moment perceptual change was also calculated following procedures used in prior research (Hard et al., 2011; Kopatich et al., 2019; Sherrill et al., 2019; Swallow & Wang, 2020). To do this, (1) videos were resized to 360 × 640 pixels; (2) for each frame, the RGB value of each pixel was extracted; (3) the Euclidean distance between each pixel in the image and the corresponding pixel in the immediately previous frame was computed; (4) the average differences across the 1s time bin was computed. This reflected the average amount of low-level perceptual change in each 1-s time bin (Sherrill et al., 2019). These scores by time bin were added to the model as a fixed factor. All models included random intercepts for subject and movie. All analyses were performed using the lme4 package (Bates et al., 2014) in R (R Core Team, 2014). R scripts for primary analyses can be found at OSF (https://osf.io/6q3yd/).

The results from this analysis are summarized in Table 7. The results show that gameplay type was a significant negative predictor of segmentation probability, such that structured videos were segmented less frequently than unstructured videos. As anticipated, completion of both A1 and A2 actions were significant positive predictors of segmentation. In terms of interactions, according to the unitization hypothesis, we hypothesized that there would be a positive interaction between domain knowledge and *A2 actions* in predicting segmentation. Conversely, according to the differentiation hypothesis, we hypothesized that there would be a positive interaction between domain knowledge and *A1 actions* in predicting segmentation. Results suggested that while domain knowledge was a nonsignificant predictor, there was a significant negative interaction between domain knowledge and A1 actions. This suggests that the likelihood of segmenting on A1 actions decreased as domain knowledge increased (see Fig. 1). All other interactions were nonsignificant.

Table 5 Means (*SD*) mention of key terms by gameplay type and domain knowledge (DK)

DK	Gameplay Type	
	Structured	Unstructured
High ($n = 43$)	0.61 (1.18)	0.28 (.68)
Low ($n = 41$)	0.11 (.43)	0.08 (.31)

DK was included as a continuous variable in analyses but is represented here using a median split

Table 7 Model estimates for the final linear mixed model predicting segmentation

	Estimate	*SE*	*z*	*p*
Fixed Effects:				
Intercept	−2.84**	0.11	−26.91	< .001
Perceptual Change	2.98**	0.44	6.84	
Gameplay Type	−0.33**	0.11	−3.10	.002
DK Score	−0.01	0.07	−0.03	.98
A1	0.39**	0.04	9.57	< .001
A2	1.19**	0.05	22.28	< .001
GP Type × DK Score	0.01	0.05	0.16	.88
A1 × DK Score	−0.09*	0.04	−2.14	.03
A2 × DK Score	0.03	0.05	0.60	.60
A1 × GP Type	0.10	0.06	1.54	.12
A2 × GP Type	0.10	0.09	1.11	.27
DK × GP Type × A1	−0.01	0.06	−0.16	.87
DK × GP Type × A2	0.05	0.09	0.59	.55
Random Effects:		*SD*		
Subject	0.36	0.60		
Item	0.03	0.16		

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

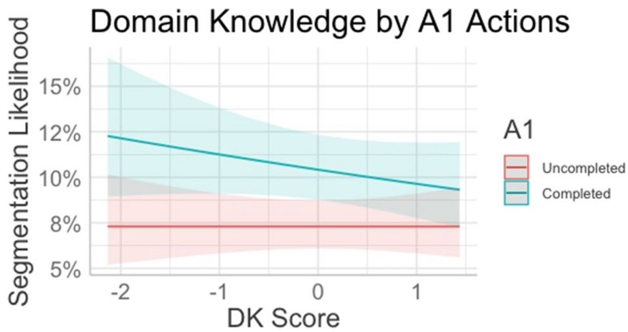

Fig. 1 Note: Interaction between domain knowledge (DK Score; centered) and segmentation likelihood for uncompleted (red) and completed (blue) A1 actions

Hypothesis testing: Event description task analyses

Mean differentiation and unitization scores by group are shown in Table 8. Two linear mixed-effects models were conducted with differentiation and unitization scores as dependent variables. Domain knowledge (continuous), gameplay type, and the interaction term (DK × Gameplay Type) were entered as independent variables, as was segmentation agreement. As mentioned, segmentation agreement has been found to be predictive of event memory (Bailey et al., 2013; Flores et al., 2017; Zacks et al., 2006). As such, we explored the extent to which segmentation agreement was related to event memory in terms of differentiation and unitization. Participant and item were entered as random effects.[3]

Results from the models are summarized in Tables 9 and 10. In terms of differentiation, results show that there were no significant predictors of differentiation scores. In terms of unitization, results show that domain knowledge was a significant positive predictor of unitization scores such that participants with higher knowledge tended to produce more phrases reflecting unitization. Conversely, segmentation agreement was a significant negative predictor of unitization, wherein participants with lower segmentation agreement scores produced more unitizations. All other predictors were nonsignificant.

Discussion

The purpose of the present study was to better understand the relationships between domain knowledge, event structure, and event segmentation in the context of highly dynamic sporting events. We were particularly interested in the extent to which people with varying degrees of domain knowledge would engage in differentiation and unitization while segmenting and recalling video content. Results will be discussed in two sections. In the first section, we discuss results from the segmentation analyses and in the second section we discuss the event description analyses.

Event segmentation

With respect to segmentation, main effects from the segmentation analyses suggested that people, regardless of their level of knowledge, segmented at changes in both A1 and A2 actions. This result is consistent with prior research suggesting that segmentation is strongly related to the hierarchical actions that comprise goals and subgoals (e.g., Kurby & Zacks, 2019; Magliano et al., 2001). Additionally, results suggested that perceptual change was a significant predictor of segmentation and that unstructured gameplay was segmented more frequently than structured gameplay. These findings are in line with previous research which shows that moment-to-moment perceptual change is predictive of segmentation (Hard et al., 2011; Kopatich et al., 2019; Sherrill et al., 2019) and that activity is segmented more frequently when viewers have a harder time deciphering an actor's goals or when the activity is more random than intentional (Wilder, 1978; Zacks, 2004).

A significant interaction between domain knowledge and A1 actions was found such that as prior knowledge increased, the relationship between A1 actions and segmentation decreased. These results are consistent with the unitization hypothesis. One possible explanation for this is that people with less knowledge engage in more differentiation, relying more on basic action changes to understand and segment activity than people with greater knowledge (Zacks et al., 2009). This may be, in part, because they have greater difficulty understanding relations among actions and making predictions about what comes next (Graziano et al., 1988; Hard et al., 2006; Zacks et al., 2009). Viewers with greater knowledge may have been able to more strongly activate the

Table 8 Means (*SD*) by gameplay type and domain knowledge (DK) for differentiation and unitization

		Diff/Unit	Gameplay Type	
			Structured	Unstructured
Domain Knowledge	High ($n = 43$)	Differentiation	2.34 (0.96)	2.30 (1.03)
		Unitization	0.98 (0.84)	0.95 (0.82)
	Low ($n = 41$)	Differentiation	2.16 (0.96)	2.20 (1.06)
		Unitization	0.68 (0.68)	0.69 (0.75)

DK was included as a continuous variable in analyses but is represented here using a median split

[3] A separate analysis was conducted in which the number of phrases produced served as a control variable. The pattern of results was similar; as such, we present the more parsimonious model here.

Table 9 Model estimates for the final linear mixed model predicting differentiation

	Estimate	*SE*	*t* value	*p*
Fixed Effects:				
(Intercept)	2.30**	0.22	10.29	<.001
DK	−0.09	0.30	−0.30	.78
Gameplay Type	−0.15	0.13	−1.14	.26
Seg. Agreement	0.05	0.14	0.38	.71
DK: GP Type	0.23	0.17	1.34	.18
Random Effects:		*SD*		
Subject	0.48	0.69		
Item	0.01	0.11		

$^{**}p < .001$, $^{*}p < .05$, $^{\dagger}p < .10$

goals of the players and anticipate the continuity of gameplay, and thereby build more hierarchically structured event models than low-knowledge viewers, though that possibility was not tested in this experiment. The prediction regarding the interaction between prior knowledge and A2 actions was not supported. A2 actions often involved the transition of the ball from a player to the basket, and it is likely that participants at all levels of knowledge were sensitive to those events.

A growing body of research has focused on how segmentation relates to higher-order goals (Bläsing, 2015; Levine et al., 2017); however, a majority of this research has focused solely on higher level goals, such as what we have been calling A2 actions, rather than changes in lower-level actions (A1 actions), and their relation to segmentation. For example, Levine et al. (2017) found that experts in figure skating were more attentive to changes in the higher-order goals that made up a figure skating routine than lower knowledge viewers when engaged in a segmentation task; however, this study did not assess the relation between lower actions and segmentation. Our study did not provide any evidence that high knowledge individuals focused more on A2 actions per se, but rather that low knowledge individuals relied more on A1 actions to build their event models. Clearly these results do not suggest that the higher knowledge viewers engaged in more differentiation than the lower knowledge viewers.

We believe that the results of the present study in conjunction with those of Newberry et al. (2021) inform the understanding of how domain knowledge relates to the propensity to engage in unitization or differentiation when segmenting an event. Newberry et al. (2021) found that participants with greater knowledge had higher segmentation agreement when instructed to reflect on the largest meaningful units of the activity than participants with less knowledge. Instructions to focus on the largest meaningful unit likely directed higher knowledge viewers to be relatively more attentive to the hierarchical goal structure of the gameplay. Interestingly, Newberry et al. found evidence that instructions to focus on the smallest meaningful unit lead to an increase in differentiation as a function of prior knowledge. Specifically, under these instructions, as prior knowledge increased, so did the frequency of detecting event boundaries. In the present study, wherein participants were not told to strategically focus on a grain size of segmentation, there was a tendency to engage in more fine-grained differentiation as knowledge decreased, which is consistent with more differentiation with less knowledge. One could imagine that different viewing activities, such as a coach or player watching a game tape, could engender a greater level of differentiation than when watching a game for pleasure. This is consistent with arguments that unitization and differentiation may operate together to varying degrees (Goldstone, 1998; Herzmann & Curran, 2011). However, understanding how other factors, such as the task and social contexts, affect how segmentation processes operate, warrants further investigation.

One final note regarding the relationship between domain knowledge and segmentation, when considering preliminary analyses, domain knowledge was not related to the quality of event segmentation as shown in the segmentation agreement analysis. What this suggests is that domain knowledge may not make someone a "better" segmenter in terms of segmenting more closely to the norm. Rather, domain knowledge appears to change the features to which a person attends when segmenting (Swallow & Wang, 2020). When experiencing an event, there is a vast amount of information in the perceptual stream and numerous ways that one could update their event model (Zacks & Tversky, 2001). Domain knowledge appears to constrain how and with what content event models are constructed. Thus, while our null result regarding segmentation agreement differences between knowledge levels may be consistent with the null effects found in prior research focused on finding differences in the regularity of segmentation as a function of domain knowledge (e.g.,

Table 10 Model estimates for the final linear mixed model predicting unitization

	Estimate	*SE*	*t* value	*p*
Fixed Effects:				
(Intercept)	0.68**	0.16	4.18	<.001
DK	0.67**	0.18	3.71	<.001
Gameplay Type	−0.03	0.14	−0.18	.86
Seg. Agreement	−0.38*	0.13	−2.96	.003
DK: GP Type	0.07	0.16	0.46	.65
Random Effects:		*SD*		
Subject	0.13	0.37		
Item	0.03	0.17		

$^{**}p < .001$, $^{*}p < .05$, $^{\dagger}p < .10$

Zacks et al., 2001; Zacks et al., 2009), it adds to the literature by suggesting that knowledge may change the features an individual attends to and utilizes to construct their event model.

Event descriptions

Previous work suggests that individuals with a high degree of domain knowledge have superior memory for domain-related information, especially when information is more structured in nature (Gobet, 2015; Sala & Gobet, 2017; Ericsson et al., 2006). Results from the current study are consistent with these findings. Participants with greater domain knowledge tended to use more domain-specific terms when describing events, especially when events were structured. This suggests that people with sufficient domain knowledge use their knowledge to interpret and understand complex events. This study adds to prior research by extending the knowledge effect to a generative task (i.e., structuring memory to create an overt description) using dynamic videos rather than static images (e.g., Allard et al., 1980; Chase & Simon, 1973).

The differentiation and unitization hypotheses were also tested using coded event descriptions. Results suggested that, while individuals did not differ in terms of engaging in differentiation during recall, individuals with greater domain knowledge tended to produce more phrases reflecting unitization than individuals with less knowledge. This finding is consistent with prior research indicating that knowledgeable individuals tend to encode dynamic event information using inherent hierarchical structures (Hard et al., 2006; Kurby & Zacks, 2011, 2012; Zacks et al., 2001). This may be seen as a form of chunking, wherein working memory load is reduced to increase storage capacity (Just & Carpenter, 1992; McGatlin et al., 2018; Radvansky, 2017).

Considerations regarding the relation between segmentation agreement and unitization

One unexpected finding was that segmentation agreement negatively predicted the use of unitization at the time of recall. One would have expected the opposite because it is straightforward to assume that segmenting activity better may be related to understanding how event parts fit together to form wholes, and then producing those wholes when reporting memories. One possible explanation is that this reflects the process of how event segmentation may organize memory for specific events. Previous research has shown a strong relationship between how well someone segments everyday events and how well they remember them (Zacks, 2020). People who segment activity more normatively tend to remember more of the events than people who segment less normatively (Kurby & Zacks, 2011, 2018; Sargent et al., 2013; Zacks et al., 2006) and produce activities more completely during action production tasks (Bailey et al., 2013). Additionally, older work has shown that participants who segment more frequently tend to recall more events (Lassiter, 1988; Lassiter et al., 1988), though that finding was not replicated in our current study. A recent study also shows that people who tend to segment better (younger adults vs. older adults) produce more differentiated descriptions of events during an online thought production task during event segmentation (Kurby & Zacks, 2019). In our study then, it is possible that segmenting more normatively is related to having more structured event representations, which may make it less likely for memories produced via recall to be summaries of event parts.

Limitations

The present study had a number of limitations. This study focused specifically on basketball. While the results share similarities with other research involving dynamic sporting events (Bläsing, 2015; Di Nota et al., 2020; Levine et al., 2017), it is possible that they may not apply to other domains. Additionally, the present study focused on segmentation within one's domain of knowledge; however, additional research should strive to compare segmentation across domains that are both within and outside of one's expertise (see Di Nota et al., 2020; Newberry et al., 2021).

Another limitation worth considering is our use of a measure of domain knowledge that assessed declarative knowledge. Such tests have been used in the segmentation literature (Newberry et al., 2021) and have been widely used in the literature on sports expertise (e.g., Herzmann & Curran, 2011; Rawson & Van Overschelde, 2008) as well as other domains (Long & Prat, 2002; Spilich et al., 1979; Voss et al., 1980). While there is a strong case for using such measures, 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 & Ericsson, 2005). As such, assessments measuring one's procedural or experienced-based knowledge are available (Bläsing, 2015; Laurent et al., 2006; see also Thomas & Thomas, 1994 for review of expertise measures). While results from the pilot study and this experiment suggest that the domain knowledge measure used here was reliable and functioned properly, it is possible that a performance-based measure of knowledge may have been more sensitive to differences in expertise. Future research may consider utilizing other measures of knowledge or a population with a high level of expertise (e.g., college basketball players).

One final limitation to consider relates to segmentation grain-size. In the present study, we were interested how people would segment events when no explicit processing goal was provided (e.g., natural viewing). As such, we did not manipulate the grain-size at which participants segmented videos (i.e., fine, coarse-grained). Prior research manipulating grain size suggests that domain knowledge may differentially affect memory for fine and coarse-grained events (Sebastian et al., 2018). Moreover, other research suggests that domain knowledge, or one's familiarity with the activity portrayed, may influence the frequency of fine-grain event boundaries and the location of coarse-grain boundaries (Newberry et al., 2021; Swallow & Wang, 2020). Future research should continue to explore how domain knowledge affects fine and coarse-grain segmentation and the implications this has on memory.

Conclusions

This study suggests that domain knowledge shapes how events are processed and understood as they unfold over time. Specifically, variability in knowledge appeared to be associated with the features that individuals attended to when segmenting and the manner in which they structured and described their experience at the time of recall. Knowledgeable individuals appeared to be (1) more likely to discriminate between structured and unstructured gameplay (see https://osf.io/uhxcb/), (2) less likely to structure their event models in terms of the process of differentiation, and, (3) more likely to use expert terms and unitizations when describing gameplay at recall.

Code availability Code for main analyses can be found online (https://osf.io/6q3yd/).

Data availability The datasets generated during and/or analyzed during the current study are available online (https://osf.io/eu7aw/).

Declarations

Conflicts of interest There are no conflicts of interest to disclose.

Ethics approval All research was approved by an institutional review board.

Consent to participate All participants completed informed consent forms before participating.

Consent for publication Not applicable

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Open practices statement The data and materials for all experiments are available online (https://osf.io/eu7aw/). This study was not preregistered.