Changes in situation models modulate processes of event perception in audio-visual narratives

Huff, M., Meitz, T. G. K., & Papenmeier, F. (in press). Changes in situation models modulate processes of event perception in audio-visual narratives. *Journal of Experimental Psychology. Learning, Memory and Cognition.*

Markus Huff

Department of Psychology, University of Tübingen

Tino G.K. Meitz

Department of Media Studies, University of Tübingen

Frank Papenmeier

Department of Psychology, University of Tübingen

Authors' Note

Markus Huff and Frank Papenmeier, Department of Psychology, University of Tübingen, Germany; Tino G.K. Meitz, Department of Media Studies, University of Tübingen, Germany.

Correspondence concerning this article should be addressed to Markus Huff, University of Tübingen, Department of Psychology, Schleichstr. 4, D-72076 Tübingen, Germany. E-mail: markus.huff@uni-tuebingen.de

Word count: 6927 words (Abstract: 207 words)

Acknowledgements

We thank G. A. Radvansky, Joseph Magliano, and two anonymous reviewers for constructive comments on an earlier version of the manuscript. We appreciated the helpful comments of Nathalie Mandel and Stephan Schwan during this research project.

Abstract

Humans understand text and film by mentally representing their contents in situation models. These describe situations using dimensions like time, location, protagonist, and action. Changes in one or more dimensions (e.g., a new character enters the scene) cause discontinuities in the storyline and are often perceived as boundaries between two meaningful units. Recent theoretical advances in event perception led to the assumption that situation models are represented in the form of event models in working memory. These event models are updated at event boundaries. Points in time at which event models are updated are important: Compared to situations during an ongoing event, situations at event boundaries are remembered more precisely and predictions about what happens next become less reliable. We hypothesized that these effects depend on the number of changes in the situation model. In two experiments, we had participants watch sitcom episodes and measured recognition memory and prediction performance for event boundaries that contained a change in one, two, three, or four dimensions. Results showed a linear relationship: the more dimensions changed, the higher recognition performance was. At the same time, participants' predictions became less reliable with an increasing number of dimension changes. These results suggest that updating of event models at event boundaries occurs incrementally.

Keywords: event perception, situation models, event boundaries, memory, prediction

Introduction

After having watched a movie, people often have the impression that they remember those parts of the story best that they found most unexpected. This suggests that there is a connection between *memory* for a specific part of the plot and spectators' ability to *predict* the future development of the plot at this specific point in time. People watching movies or dynamic activities generally segment the continuous stream of information into discrete events (Newtson, 1973). Between two such events, human observers perceive an *event boundary*. Thus, event boundaries are points in time where things change. Event boundaries are important for *memory* (Newtson & Engquist, 1976) and *prediction* about future behavior (Zacks, Kurby, Eisenberg, & Haroutunian, 2011). Recent advances in event perception theory suggest that *event models,* representing the ongoing observation in working memory, guide the perceptual processing of dynamic events (Zacks, Speer, Swallow, Braver, & Reynolds, 2007). These event models are updated whenever participants perceive an event boundary. Event models can be conceived as *situation models* that enable the description of a specific situation using five dimensions – time, location, character, intention, and causation (Zwaan, Langston, & Graesser, 1995). In two experiments, we investigated how situation model changes in up to four dimensions at event boundaries influenced participants' memory for these events and how they influenced participants' ability to predict future events. More specifically, we address the question of how the working memory representation of an ongoing event is updated at event boundaries.

Event segmentation

When observing everyday activities, such as somebody preparing breakfast, continuous information is available to the sensory systems. However, memory for such events is typically segmented into discrete events like switching on the coffeemaker, fetching milk and marmalade from the refrigerator, setting the table, etc. Newtson (1973) has shown that human observers segment the continuous stream of such events into discrete events. He asked participants to simply press a button when they presume that one meaningful event has ended and another meaningful event begins. Segmentation behavior was shown to be influenced by prior knowledge of the observer or predictability of the observed events (for an overview see Schwan & Garsoffky, 2008). Event segmentation theory (EST; Zacks et al., 2007) builds on the observation that perception is non-continuous and proposes that humans predict in order to perceive. These predictions are based on event models that represent ongoing behavior in working memory. As long as these predictions are consistent with the actual ongoing activity, the *event model* of what is happening at the moment remains stable and valid. Observers perceive these periods of stability as coherent events. However, from time to time prediction and reality disaccord, i.e., prediction errors increase. The consequence is the impression of an event boundary and the updating of the event model. Therefore, the current event model in working memory has to be updated. For this to happen, a gating mechanism opens and sensory inputs are transiently processed more thoroughly in order to build a new event model (Zacks et al., 2007).

Situation models in event perception

Event models can be conceived as *situation models* known from narrative comprehension literature (Zacks et al., 2007). The concept of situation models was originally developed to explain how people understand narrative texts (van Dijk & Kintsch, 1983). Situation models are defined as mental representations of what a narrative text is about. They focus on the situation described in a text, rather than the structure of the text itself (Zwaan, 1999). According to the *event indexing* (EI) model by Zwaan et al. (1995), readers of narrative texts decompose each incoming event (indicated by a verb) into five indexes: time, location, character, intention, and causation. When a new event begins, it must be integrated into the current situation model. This is more demanding the fewer indexes both situation models share. For example, if the incoming event occurs at a later point in time, but at the same place with the same characters, the event is easier to integrate than if it contained additional changes in characters or location (Zwaan et al., 1995). Thus, according to the EI model, processing load during comprehension should increase with a growing number of situation changes (*additivity hypothesis*; Zwaan & Radvansky, 1998). Evidence for this hypothesis comes from several studies showing that reading times increase and coherence ratings decrease as a function of the number of changes in the current situation model (Rinck & Weber, 2003; Zwaan, Magliano & Graesser, 1995; Zwaan, Radvansky, Hilliard & Curiel, 1998).

There is reliable evidence for the similarity of situation models of EI and event models of EST. Magliano, Miller, and Zwaan (2001) specifically tested the validity of the EI model in the context of film understanding. They analyzed shots (i.e., continuous runs of the camera) of a movie with regard to the dimensions *time* and *location*. The authors asked their subjects to watch a movie and concurrently segment it into separate meaningful units (i.e., events). Results indicated that shifts in time or movement of characters were sufficient to create a change in the current situation model. Both dimensions made independent contributions to situation-model construction. In contrast, shifts in region could only create a new situation when they co-occurred with temporal ellipses. There was also evidence for the *additivity hypothesis*: multiple dimension changes had an additive effect on situation-change judgments (see also Zacks, Speer, & Reynolds, 2009).

Taken together, these findings support the assumption that the probability of the perception of an event boundary increases whenever a change in one or more dimensions of the current event model occurs. Furthermore, it seems reasonable to assume that event boundaries can vary in strength, depending on the number of situational shifts they involve (additivity hypothesis).

Event boundaries and memory

The concept of event boundaries is closely related to memory for events. Newtson (1973) originally claimed that the number of event boundaries is an indicator of the amount of information an observer extracts from an ongoing event. More specifically, Newtson and Engquist (1976) have shown that after watching a film, frames from event boundaries were recognized better than those from non-boundaries. The presence of clearly perceivable event boundaries is also important for memory of filmic summaries (Schwan & Garsoffky, 2004) and instructions (Mura, Petersen, Huff, & Ghose, 2013; Zacks & Tversky, 2003).

Zacks, Speer, Vettel, and Jacoby (2006) have shown that people who showed a more idiosyncratic manner of segmenting activity (that is, who differed in their perception of event boundaries from most other people) also had deficits in recognition memory for this activity and in memory for the temporal order of events. The authors showed that event segmentation is one good predictor for event memory. Moreover, Speer and Zacks (2005) argued that event segmentation could be a form of memory control. They conducted a study in which participants read clauses of narrative texts that contained temporal shifts. The authors found that these temporal shifts increased the likelihood of perceiving an event boundary. This in turn reduced the availability of recently presented information in memory. Following a temporal shift like “a moment later…”, participants were less likely to correctly identify a word from a previous sentence than when no temporal shift occurred. This means that when encountering an event boundary, information from the previous event is less likely to be relevant; thus, it does not need to remain highly activated. Similar results for audiovisual stimuli are reported by Swallow, Zacks, and Abrams (2009). Their participants watched movie clips that were stopped once in a while. After each stop, they performed a two-alternative forced choice recognition test for either objects or events. In the object test, two pictures appeared on the screen: one depicted an object that was seen five seconds earlier in the clip, the other depicted an object that was not seen in the clip but was contextually appropriate. In the event test, a question about what had happened five seconds earlier appeared on the screen, along with the right answer and a reasonable alternative answer. Participants decided which of the two objects they had just seen in the clip or which of the two statements correctly answered the question. There were two important factors: 1) an event boundary vs. no event boundary occurred while the object was visible in the clip (boundary objects vs. non-boundary objects); 2) an event boundary vs. no event boundary occurred in the delay between the object presentation in the clip and the test (objects were seen in the previous vs. in the current event). Results showed that non-boundary objects were remembered less well when they appeared in previous events than in current events. However, boundary objects were remembered equally well in previous and current events.

Taken together, these findings demonstrate that the perception of event structures is strongly connected to memory for these events. At event boundaries, perceptual information receives additional relational and associative priming (Swallow et al., 2009) and is therefore encoded more deeply in memory. In contrast, information from previous events tends to be less accessible because event models are updated at event boundaries.

Event boundaries and prediction

Predictions allow humans to anticipate future actions of an interaction partner or future developments of a narrative plot. However, it is a matter of debate whether participants make predictions during event perception – for example when reading texts, observing goal directed activities, and watching movies. Whereas previous text comprehension research suggests that predictions are rather weak and some of the reported effects might be due to methodological shortcomings and thus be better explained with “backwards mapping” (i.e. participants base their decisions on evaluations of an item at the time it is presented and check if this is a plausible outcome; Potts, Keenan, & Golding, 1988), recent psychophysiological research using event-related potential found evidence, that text comprehension is actually based on making predictions of semantically defined classes of words (Szewczyk & Schriefers, 2012). Using visual narratives, Cohn and Paczynski (2013) showed that processing of agent information triggered predictions about future events. In Experiment 2 of their study, participants were presented with visual narratives, which either depicted the *agent* (e.g., *Charlie Brown*) or the *patient* (e.g., a ball) panel of an action first. Participants answered the question “What will happen next?”. In the agent condition more “prediction answers” (i.e. participants’ answers were in line with the actual outcome of the visual narrative) were observed than in the patient condition.

According to EST, *errors in prediction* play the central role in event structure perception. Transient increases in prediction errors lead to the formation of event boundaries (Zacks et al., 2007). Zacks et al. (2011) had participants watch movies of different naturalistic activities. From time to time, the movie was stopped and participants decided if the activity depicted on a photograph would depict the activity five seconds later. The authors found that prediction was slower, less accurate and made less confidently across event boundaries than within events. Reynolds, Zacks, and Braver (2007) exposed a neural network to sequences of recurrent actions and trained it to predict the next input. They found that prediction error was sufficient to identify event boundaries, and that prediction performance improved when prediction error guided the updating of event representations. It is important to note that predictions in EST are based on continuity of the event model in working memory. As long as there is no perceptual change the cognitive system predicts continuity.

To summarize, these findings demonstrate that event boundaries do not only play a central role for memory but also for the ability to make predictions about future events.

Experimental overview and hypotheses

In two experiments, we investigated the influence of the number of dimension changes of the current event model on processes of event perception. The specific manipulation of dimension changes in the current event model allows for predictions of subsequent perceptual and cognitive processes in event perception. More specifically, we aim to test the influence of changes in the event model on participants' memory and their ability to predict future events. We used two sitcom episodes as stimulus material. In a first step, we asked participants to segment each episode into single meaningful units. This way, we identified the most prominent event boundaries and analyzed them with regard to changes in the event model dimensions: character, time, location, and action. We then defined four types of event boundaries: event boundaries with one, two, three, and for dimension changes. In the *memory* experiment, we measured recognition memory for event boundary pictures after subjects had seen the movies. In the *prediction* experiment, we stopped the movies shortly before event boundaries and asked subjects to predict what might occur on the screen in five seconds.

This setup allowed us to test two competing hypotheses. The *incremental updating hypothesis* is based on the additivity hypothesis of EI theory (Zwaan et al., 1995) and assumes that changes in the event model trigger specific updating processes in the corresponding dimensions representing the event (e.g., a character entering the scene specifically updates the event model dimension character). That is, updating effort increases linearly with increasing number of dimension changes. If this is true, memory and prediction performance should show a linear pattern too; memory performance for event boundary information should increase linearly with increasing dimension changes. At the same time, prediction performance about the future development of the plot should decrease linearly.

In contrast, the *global updating* hypothesis, which is based on EST predicts complete updating of event models at event boundaries (Zacks et al., 2007). That is, information represented in the dimensions of the current event model is reset and has to be updated at the beginning of a new event. In this case, there should be no difference in memory and prediction performance with regard to the number of dimensions that change at event boundaries.

Segmentation Task

The goal of the segmentation task was to determine event boundaries for the memory and prediction experiments.

Method

Participants. Twenty-two students of the University of Tübingen participated in this experiment for course credit or monetary compensation. All watched the episodes for the first time and had normal or corrected to normal vision. Their first language was German.

Material and apparatus. Stimulus material consisted of three sitcom episodes. We used two episodes from the sitcoms (*sit*uational *com*edy) “Big Bang Theory” (BBT; Lorre & Cendrowski, 2007) and “Two and a Half Men” (MEN; Lorre & Aronsohn, 2003) as experimental stimulus material. In addition, we used a 3-minute clip from the sitcom “Friends” (Crane & Kauffman, 1994) as a practice film. We used the German-dubbed versions of the sitcoms. Each episode lasted approximately 15 minutes and was edited such that it contained no logos or lettering. The experiment was programmed in E-Prime 2.0 (Psychology Software Tools, Inc.; Schneider, Eschman, & Zuccolotto, 2002). The sitcoms were presented on a 24” display. Participants’ responses were recorded with a DirectIN button box (www.empirisoft.com).

Procedure. Participants performed a classical segmentation task (Netwson, 1973): they watched each sitcom and pressed a button on the button box to indicate when, in their opinion, one meaningful unit ended and another one began. Participants first watched the practice sitcom and then the two experimental sitcoms in a randomized order. They completed the segmentation task once for the largest (coarse segmentation) and once for the smallest (fine segmentation) meaningful units, whereby we counterbalanced the temporal order. The instruction stated the following:

"(…) In this part of the experiment, we will ask you to perform the following task while watching a total of three movies. Please segment the storyline into the smallest (largest) units that seem natural and meaningful to you. There is no right or wrong manner of doing this: we are just interested in the way you perform this task. To mark the boundaries between two small (large) units, please press the yellow button. Please make sure you press the button as close as possible to the end of a unit. Do not press the button in the middle of a unit. Please remember that there is no right or wrong way to mark these units, just make sure to press the button when – in your opinion – a small (large) natural and meaningful unit ends and another one begins. (…)"

Results

We analyzed segmentation data similar to Zacks, Kumar, Abrams, and Mehta (2009). We first divided the movies into 1-second intervals. This resulted in 907 intervals for MEN and 961 intervals for BBT. For each interval, we counted the number of participants who had pressed a button for either a fine or a coarse event boundary, resulting in two time series (one for fine and one for coarse segmentation). We then divided both frequency time series by their standard deviations and summed them up (see Zacks et al. 2009). This way we combined fine and coarse event boundaries into one time series, representing a standardized measure of segmentation magnitude for each clip (*segmentation magnitude*; see Figure 1).

Event boundaries. We analyzed each event boundary with regard to changes in the event model, using the dimensions time, location, character, and action (cf. Zacks & Magliano, 2011). A time change was defined as the activity after the event boundary being time-delayed in comparison to the activity before the breakpoint (i.e. temporal omissions). Changes in location involved transitions between rooms or other clearly defined spatial areas (e.g., from the kitchen area to the living room area in a large room). A character change was defined as one or more persons either leaving or entering the scene. Action changes were defined as a new action being depicted after the event boundary. This also involved changes in the topic of conversation. This way we obtained event boundaries with one, two, three, or four dimension changes (see Table 1). We selected event boundaries with the highest possible segmentation magnitude that were dispersed as equally as possible over both clips. This resulted in in 16 event boundaries for BBT (2 boundaries with 1 change; 6 boundaries with 2 changes; 4 boundaries with 3 changes; 4 boundaries with 4 changes) and 13 event boundaries for MEN (4 boundaries with 1 change; 5 boundaries with 2 changes; 0 boundaries with 3 changes; 4 boundaries with 4 changes; see also Appendix A). There was a filmic cut at each selected event boundary. There was a significant positive correlation between segmentation magnitude and number of dimension changes at an event boundary, $r = .72$, $t(27) = 5.35$, $p < .001$ (see Figure 2). Finally, we calculated the correlations between the dimension changes of the selected event boundaries (see Table 2). Only the positive correlation between the dimensions time and location ($r = .76$) was statistically significant, $t(27) = 6.03$, $p < .001$.

Memory Experiment

In the memory experiment, we presented participants with the sitcom episodes MEN and BBT and measured recognition memory for pictures recorded at the selected event boundaries. We predicted the following results for the first experiment: first, according to the additivity hypothesis of event indexing (Zwaan et al., 1995), recognition memory for pictures should increase linearly with the number of dimensions changed at the event boundary from which the pictures were taken.

In contrast to some other studies that investigated memory in combination with event segmentation (e.g., Lassiter, Stone, & Rogers, 1988; Zacks, et al., 2006), our participants did not perform a segmentation task while watching the movies. The reason for this is that EST refers to event segmentation as an automatic process (Zacks et al., 2001). Thus, we presumed that memory for event boundary pictures should not depend on the instruction to segment the movie clips during encoding.

Method

Participants. Twenty-eight students of the University of Tübingen participated in this experiment for course credit or monetary compensation. We excluded data of 3 participants because they reported having seen both of the two sitcom episodes before. Further, there were 4 participants who have reported that they have seen one of the two sitcom episodes before (1 MEN and 3 BBT). We excluded the respective subsets of the data. In total, complete data of 21 participants and data subsets of 4 participants entered final analyses. All participants had normal or corrected to normal vision. Their first language was German.

Material and apparatus. Stimulus material and apparatus was similar to the segmentation task with the following exceptions. The recognition test of BBT comprised 32 picture items (16 target and 16 distractor pictures). The recognition test of MEN comprised 26 pictures (13 target and 13 distractor pictures). Target pictures were screenshots depicting the scenes immediately after the respective event boundaries. The delay between event boundary and picture was about 1 s. The distractor pictures were taken from a different episode of the same sitcom, depicting a similar scenery or an appropriate connection to the antecedent event

Procedure. The experiment began with a short practice task in which participants watched a 3-minute clip of the sitcom *Friends* (Crane & Kauffman, 1994) and performed a short visual recognition test. The main experiment contained two blocks, one for each sitcom (BBT, MEN). The temporal order of the blocks was counterbalanced between participants. One block consisted of a learning phase (viewing the clip) and a test phase (performing the recognition task). Participants were seated in front of a computer and began by reading the following short instruction:

"(…) You are going to watch two episodes of the sitcoms *Big Bang Theory* and *Two and a Half Men*. After each episode, we will show you several pictures one after another. Please decide for every single picture if you saw it in the episode that you just watched. (…) Press the right (left) button for "yes, I saw it" and the left (right) button for "no, I did not see it". Please make your decisions as fast, yet as accurately, as possible (…)."

They subsequently watched one of the two sitcoms. At the end of the film, they were presented with the target and distractor pictures one after the other in a random order. They were asked to press one of the two outer keys (left/right) on the button box to indicate whether they had seen the depicted scene in the sitcom or not. Response side was counterbalanced between participants. There was no time limit for the responses. However, we instructed participants to respond as quickly and as accurately as possible. After the recognition task, they informed the experimenter, who then started the second block. They were allowed to take a short break between the two blocks. The second block proceeded identically to the first block. At the end of the second block, participants indicated whether they had seen any of the movies before. Altogether, the experiment lasted about 45 minutes.

Results

We pooled data across both sitcoms. We analyzed the data with linear mixed effect models (lme; Baayen, 2008; Pinheiro, Bates, DebRoy, Sarkar, & R Development Core Team, 2011). We fitted linear mixed effect models (lme models) with random intercept for the *participant*-effect for each dependent variable.

Hit rate. Data are plotted in Figure 3. Overall accuracy for the target pictures (for each subject) was high (M = .91, SD = 0.08) and increased linearly with increasing number of dimension changes.

As a first step in the model selection process, we fitted a model with intercept as fixed effect, suggesting no difference between conditions (AIC: 197.99) and compared it with a model with dimension change as continuous fixed factor. (AIC: 193.74). A likelihood-ratio test revealed significant differences in goodness-of-fit between the two models, χ^2 (1) = 6.25, p = .012. Thus, we retained the latter model with dimension change as continuous fixed effect. Next, we compared this model with a model with four fixed effects (one for each condition; AIC: 196.17). A likelihood ratio-test revealed no significant difference χ^2 (1) = 1.57, p = .457; thus, we retained the simpler model with two fixed effects (intercept and slope of the dimension change factor. The intercept (0.87) indicates estimated performance in the condition with one dimension change. The slope (0.03) indicates that recognition performance increases by 3% with each additional change in a dimension of the event model. Taken together, the data are in line with predictions from the additivity hypothesis of EI (Zwaan et al., 1995), which assumes a linear relationship between the number of dimension changes and recognition performance (results are presented in Table 3).

Response times. We analyzed response times for hits (i.e. yes-answers to target items). We excluded response times longer than 7500 ms (1 trial, 0.17% of the data). The descriptive data are plotted in Figure 4. The procedure was similar to the analysis of accuracy; therefore we report only the results at this point.

There were no significant differences between the intercept model (AIC: 9346.50), the linear model including the two fixed parameters intercept and slope (AIC: 9346.20), and the model with four fixed effects (one for each dimension change condition, AIC: 9347.60), largest $\chi^2(1)$ = 2.62, smallest p = .129. Thus, we retained the intercept model assuming no differences in response times between the conditions. The intercept (1444) indicates the mean response time of hits in milliseconds across all dimension change conditions. Results of the intercept model are shown in Table 4.

Discussion

In the memory experiment, we examined the hypothesis that memory for event boundaries increases with an increasing number of dimension changes of the current event model (additivity hypothesis). We identified event boundaries with one, two, three, and four changes in the dimensions of the event model. Participants viewed episodes of sitcoms and subsequently performed a visual recognition test. Results confirmed the additivity hypothesis: visual recognition performance increased linearly with the number of dimension changes. At the same time, response times of hits did not differ across the conditions of the factor dimension changes.

Prediction Experiment

In the prediction experiment, we investigated people's ability to make predictions as a function of the respective event model in working memory. Our hypotheses are that predictions across event boundaries should become less accurate with the number of dimension changes in the current event model.

Method

Participants. Forty-six students of the University of Tübingen participated in this experiment for course credit or monetary compensation. We excluded data of 5 participants because they reported having seen both of the two sitcom episodes before. Further, there were 14 participants who have reported that they have seen one of the two sitcom episodes before (3 MEN and 11 BBT). We excluded the respective subsets of the data. In total, complete data of 27 participants and data subsets of 14 participants entered final analyses. All participants had normal or corrected to normal vision. Their first language was German.

Material and apparatus. Stimulus material and apparatus were similar to the memory experiment with the following exceptions. We divided both sitcoms into multiple units by pausing them every 2500 ms before an event boundary. This resulted in 17 units for BBT and 14 units for MEN. In addition, we created two types of pictures for each event boundary: one target and one distractor picture. Target pictures were screenshots taken 2500 ms after the event boundary. Thus, the target pictures depict the plot 5000 ms after the sitcom was paused. Corresponding distractor pictures were screenshots taken 1000 ms after the next event boundary (see Figure 5). For the final event boundary of each film, distractor pictures were taken from immediately before the sitcom ended. As in the memory experiment, target and distractor pictures depicted identifiable scenes with at least one actor. The experiment was programmed using PsychoPy 1.78.01 (Peirce, 2009).

Procedure. As in the memory experiment, participants practiced the task by watching the same 3-minute clip of the sitcom *Friends*. For the main experiment, they watched the same sitcoms as in the memory experiment. Each video stopped 2500 ms before an event boundary. Immediately after the stop, either a target or a distractor picture appeared in random order. Participants decided if the picture depicted the activity in the sitcom five seconds later. They pressed a button labeled “j” for a target response or a button labeled “n” for a distractor response. Then the video continued and stopped again 2500 ms before the next breakpoint. Participants could take a short break between the two sitcoms. Finally, participants indicated whether they had seen any of the episodes before. All in all, the experiment lasted about 45 minutes.

Results

Data analysis was similar to the memory experiment. We pooled the data across both sitcoms (BBT, MEN). Further, we fitted linear mixed effect models with random intercept for the *participant*-effect for each dependent variable.

Hit rate. Mean prediction hit rate was M = .82 (SD = 0.28). Descriptive data are plotted in Figure 6.

First, we fitted a model with intercept as fixed effect. This model assumes no differences in prediction performance between the conditions (AIC: 349.53). We compared this model with a model that included the factor dimension change as continuous fixed effect (AIC: 325.34). As in the memory experiment, there was a significant difference between these models, χ^2 (1) = 26.19, p < .001. Thus, we retained the latter model.

Second, we compared this model with a model with four fixed effects (one for each dimension change condition) that treated the factor dimension change categorical fixed effect (AIC: 328.58). Yet, this lme model did not provide a better fit to the data than the lme model that included the two factors as main effects (AIC: 823.76), χ^2 (2) = 0.76, p = .683. Thus, we retained the model with intercept and slope as fixed effects assuming a linear relationship between the number of dimension changes and prediction performance (Table 5). The intercept (0.96) indicates estimated performance in the condition with one dimension change. The slope (-0.09) indicates that prediction performance decreases by 9% with each additional change in a dimension of the event model.

Response times. We analyzed response times for hits (i.e. correct responses to target items). We excluded response times longer than 7500 ms (10 trials, 3.32% of the data). Mean response time was M = 2575 ms (SD = 1024 ms). Again, the analysis was the same as for the hit rate. As can be seen in Figure 7, response times increased linearly with increasing number of dimension changes.

First, we tested for differences between the intercept model (AIC: 4915.70) and a model with number of dimension changes as continuous fixed effect (AIC: 4912.6). The latter model assuming a linear relationship between number of dimension changes and response times provided a better fit than the intercept model, χ^2 (1) = 5.08, p = .024.

Second, we tested this model with two fixed effects (intercept and slope) against a model with four fixed effects (one for each dimension change condition; AIC: 4914.6). Likelihood-ratio tests revealed no significant differences between these models. Thus, we retained the simpler model with two fixed effects, assuming a linear relationship between number of dimension changes and response times (see Table 6). The intercept (2411) indicates estimated performance in the condition with one dimension change. The slope (135) indicates that response times of hits increase by 135 ms with each additional change in a dimension of the event model.

Taken together, prediction performance declined linearly (decreasing hit rate, increasing response times) with increasing number of dimension changes. As in the memory experiment, the prediction data are in line with predictions from the additivity hypothesis of EI (Zwaan et al., 1995) assuming a linear relationship between the number of dimension changes and prediction performance.

Discussion

The goal of the prediction experiment was to test observers' ability to predict future events. In this experiment, we paused the sitcom before an event boundary with one, two, three, or four changes in the event model. We hypothesized that predictions would become less accurate with an increasing number of dimension changes of the current event model. Results confirmed our hypothesis; we observed a linear relationship between the number of dimension changes and the dependent measure hit rate. The more dimensions changed, the lower prediction performance was. At the same time, we observed longer response times with increasing numbers of dimension changes. Thus, we can exclude biasing effects such as a speed-accuracy trade-off as an alternative explanation.

These results clearly extend the finding of Zacks et al. (2011), who showed that predicting the near future is impaired at event boundaries. In the Zacks et al. study it was not possible to differentiate between different kinds of event boundaries because the stimulus material consisted of continuous films of everyday actions like washing a car. These films did not contain the range of dimension changes we examined in our study. By examining the dimensions time, character, location, and action at event boundaries, we were able to show specific effects on the updating process at event boundaries.

These results show that humans make predictions based on current event models. More specifically, the results support the assumption that the event models that represent the current observations in working memory are not completely reset at event boundaries but updated incrementally.

General Discussion

Points in time at which certain aspects of an observed event change are important for perception and cognitive processes. Such changes can be described using the dimensions of the situation model concept (Zwaan et al., 1995). Whenever one or more dimensions change, observers perceive an event boundary. Event boundaries are stronger the more dimension change at the same time (*additivity hypothesis*; Zwaan & Radvansky, 1998). However, whereas the additivity hypothesis has been investigated and confirmed with respect to the formation of event boundaries (e.g., Zwaan et al., 1995; Zwaan et al.,1998), there is – to our knowledge – no study that tested the predictions of the additivity hypothesis for cognitive processes. In that sense, the current study investigated two basic cognitive processes in the perception of dynamic events, namely *memory* for an event and the ability to *predict* future events. More specifically, we hypothesized that memory for a certain event boundary is higher the more dimensions have changed. Further, the ability to make predictions across event boundaries should suffer the more dimensions change. Results of the two reported experiments confirmed this hypothesis. We found a consistent influence of the number of dimension changes in the current event model on memory and prediction performance. Memory and prediction performance both varied as a linear function of the number of situational changes. More specifically, they were diametrically opposed.

Our results relate to current theories of event perception like EST (Zacks et al., 2007), which describes human event perception as a process that relies on making predictions about the future development of an event. These predictions are based on event models that represent the currently observed activity in working memory. An error detection mechanism reacts to transient increases in prediction error by causing a gating mechanism to open. As a consequence, perceptual input is temporarily processed more elaborately in order to build up a new event model. This deeper processing is very likely to result in better memory for information from event boundaries, as could be shown in several studies (e.g., Baird & Baldwin, 2001; Hanson & Hirst, 1989, 1991; Huff, Papenmeier, & Zacks, 2012; Lassiter, 1988; Lassiter & Slaw, 1991; Lassiter, Stone, & Rogers, 1988; Newtson & Engquist, 1976; Schwan & Garsoffky, 2004; Zacks et al., 2006). Besides effects on memory, perception of an event boundary also impairs the ability to predict future developments of the observed action. Zacks et al. (2011) demonstrated that participants were able to make reliable predictions about the future as long as they were restricted to the same events. However, predictions across event boundaries were less accurate. According to EST, the event model is updated in a global manner. Thus, no information is transferred across an event boundary. This is in contrast to the EI theory, which proposes that situation models are updated incrementally at points of change (e.g., Zwaan et al., 1998).

In the segmentation experiment we replicated the finding that an increasing number of dimension changes is related to higher segmentation magnitude (i.e. the number of participants who perceived an event boundary in a specific interval). However, and most importantly, we showed that the number of dimension changes is predictive for memory and the ability to predict future events. Thus, if the updating of the event model is related to an increased processing of sensory information, ultimately leading to higher memory for these points in time (Zacks et al., 2007), we can conclude that this updating process is selective for those dimensions of the event model that changed at this point. In the same vein, if the event model is reset at an event boundary, prediction performance should be independent of the number of dimensions that have changed. However, we found that prediction performance decreased linearly with an increasing number of dimension changes.

The fact that we found gradation in both recognition memory and prediction performance suggests that the updating of event models does not take place in an all-or-nothing manner, but instead incrementally. This finding is contradictory to Kurby and Zacks' (2012) results. The authors found evidence that readers of narrative texts update their situation models incrementally within an event, but globally at event boundaries. It should be noted that there were some differences in the experimental designs. First, dependent variables in Kurby and Zacks' study were think-aloud responses, because they assumed that a situational dimension that is currently being updated should very likely be mentioned in a verbal report. By contrast, in our study we directly measured memory and prediction performance. Second, stimulus material in Kurby and Zacks' study consisted of a text describing a day in the life of a boy (Barker & Wright, 1951), whereas we used audio-visual narratives. It is important to note, however, that differences in the internal structure (ethnographical description vs. narration) are more important for differences in event processing than differences in medium (text vs. film; Magliano, Kopp, McNerney, Radvansky, & Zacks, 2013).

We believe that it is more reasonable to expect incremental rather than global updating at event boundaries. First, it seems more effective to update only those dimensions that change not only within an event but also at event boundaries, especially with regard to the assumption that event segmentation is a form of cognitive control (Speer & Zacks, 2005). In line with the EI model, we presume that updating occurs only for changing dimensions and that unchanged information is not updated. According to this view, the gating mechanism postulated by EST would be more specifically connected to the error detection mechanism. More specifically, the error detection mechanism sends signals about prediction errors in the respective dimensions, and the gating mechanism opens only for information from those dimensions. This is a reasonable explanation for the results of the memory experiment: the higher the number of dimensions that change, the more perceptual information arrives through the gating mechanism to form a new event model. This increased processing effort is related to deeper processing of the respective situation. The results of the prediction experiment are in line with this point of view. Predictions become less reliable with an increasing number of dimension changes.

Not every change in the dimensions of the current event model is unexpected to the observer. For example, a character change might be anticipated if an actor stands up and walks to the door. Yet, there is some uncertainty with respect to the further development of the plot. For example, the next shot could depict this actor at a new location (e.g. in an adjacent room) or it could depict the remaining actors in the original location. Further research is needed to examine the nature of such event boundaries and its influence on event perception processes.

In the current study, we examined processes of event perception, using edited films as stimulus material. Films differ from real life in various ways. There are filmic cuts, camera pans, and temporal ellipses. Although research has shown that filmic cuts including abrupt viewpoint changes hinder visual processing and affect memory for artificial dynamic scenes (Garsoffky, Huff, & Schwan, 2007; Huff, Jahn, & Schwan, 2009; Huff, Meyerhoff, Papenmeier, & Jahn, 2011), there is some evidence that experienced viewers have no problems in following a plot despite severe disruptions of the perceptual process (Germeys & d'Ydewalle, 2007; Huff & Schwan, 2012; Schwan & Ildirar, 2010; Smith & Henderson, 2008). Further, filmic cuts might disrupt the depicted action. Magliano and Zacks (2011) showed that filmic edits with changes in action had greater influence on participants' segmentation behavior than edits with shifts in time and/or location. In the current study, all event boundaries were related with a filmic cut and all except for one depicted action changes. This is probably a by-product of the method we used to select the event boundaries. Thus, the conclusions of the current study are restricted to cognitive processes at event boundaries depicting action changes. Given these properties – which involve sudden changes in event model dimensions after a cut and the ability to easily follow the plot – we believe that films are a good tool in studying processes of event perception. Further research is needed to examine specific influences of event boundaries with no action change but changes in time, location, and/or character on memory and prediction. Depending of the kind of dimension change (or combinations thereof) we would expect differential influences on cognitive processes (Scott-Rich & Taylor, 2000).

Conclusion

When perceiving and understanding unfolding events, human observers segment ongoing behavior into discrete events at points of change. These experiments have demonstrated that changes in one ore more dimensions of the current event model are perceived as event boundaries, eventually influencing basic processes of event perception. An increasing number of dimension changes is related to higher memory for this specific point in time and lower ability to predict future events. Dimension changes trigger updating processes of the current event model in working memory. Summarizing, we propose that event models (situation models) are updated incrementally at event boundaries and that EST (Zacks et al. 2007) might need to be adapted accordingly.

References

Baird, J. A. & Baldwin, D. A. (2001). Making sense of human behavior: Action parsing and intentional inference. In B.F. Malle, L.J. Moses, & D.A. Baldwin (Eds.). *Intentions and intentionality: Foundations of social cognition* (pp. 193-206). Cambridge, MA, US: The MIT Press.

Baggett, P. (1984). Role of temporal overlap of visual and auditory material in forming dual media associations. *Journal of Educational Psychology*, *76*(3), 408–417.

Barker, R. G., & Wright, H. F. (1951). *One boy's day: A specimen record of behavior*. New York: Harper & Brothers.

Cohn, N., & Paczynski, M. (2013). Prediction, events, and the advantage of Agents: The processing of semantic roles in visual narrative. *Cognitive Psychology*, *67*(3), 73–97. doi:10.1016/j.cogpsych.2013.07.002

Crane, D., & Kauffman, M. (1994). *Friends* [Motion picture]. USA: Warner Bros. Television.

Garsoffky, B., Huff, M., & Schwan, S. (2007). Changing viewpoints during dynamic events. *Perception*, *36*(3), 366–374. doi:10.1068/p5645

Germeys, F., & D'Ydewalle, G. (2007). The psychology of film: perceiving beyond the cut. *Psychological Research*, *71*(4), 458–466.

Hanson C, & Hirst W. (1989). On the representation of events: A study of orientation, recall, and recognition. *Journal of Experimental Psychology: General, 118*(2), 136–147.

Hanson C, & Hirst W. (1991). Recognizing differences in recognition tasks: A reply to Lassiter and Slaw. *Journal of Experimental Psychology: General*, *120*(2), 211–12.

Huff, M., Jahn, G., & Schwan, S. (2009). Tracking multiple objects across abrupt viewpoint changes. *Visual Cognition*, *17*(3), 297–306. doi:10.1080/13506280802061838

Huff, M., Meyerhoff, H. S. S., Papenmeier, F., & Jahn, G. (2010). Spatial updating of dynamic scenes: Tracking multiple invisible objects across viewpoint changes. *Attention, Perception, & Psychophysics*, *72*(3), 628–636. doi:10.3758/APP

Huff, M., Papenmeier, F., & Zacks, J. M. (2012). Visual target detection is impaired at event boundaries. *Visual Cognition*, *20*(7), 848–864. doi:10.1080/13506285.2012.705359

Huff, M., & Schwan, S. (2012). Do not cross the line: Heuristic spatial updating in dynamic scenes. *Psychonomic Bulletin & Review*, *19*(6), 1065–1072. doi:10.3758/s13423-012-0293-z

Kurby, C. A., & Zacks, J. M. (2012). Starting from scratch and building brick by brick in comprehension. *Memory & Cognition*, *40*(5), 812–26. doi:10.3758/s13421-011-0179-8

Lassiter G.D. (1988). Behavior perception, affect, and memory. *Social Cognition, 6*(2), 150–176.

Lassiter G.D., & Slaw R.D. (1991). The unitization and memory of events. *Journal of Experimental Psychology: General, 120*(1):80–82.

Lassiter, G. D., Stone, J. I., & Rogers, S. L. (1988). Memorial consequences of variation in behavior perception. *Journal of Experimental Social Psychology*, *24*(3), 222-239. doi:10.1016/0022-1031(88)90037-6

Lorre, C., & Aronsohn, L. (2003). *Two and a half men* [Motion picture]. USA: Warner Bros. Television.

Lorre, C., & Cendrowski, M. (2007). *The big bang theory* [Motion picture]. USA: Warner Bros. Television.

Magliano, J., Kopp, K., McNerney, M. W., Radvansky, G. A., & Zacks, J. M. (2012). Aging and perceived event structure as a function of modality. *Aging, Neuropsychology, and Cognition*, *19*(1-2), 264-282.

Magliano, J. P., Miller, J., & Zwaan, R. A. (2001). Indexing space and time in film understanding. *Applied Cognitive Psychology*, *15*(5), 533-545. doi:10.1002/acp.724

Mura, K., Petersen, N., Huff, M., & Ghose, T. (2013). IBES: A tool for creating instructions based on event segmentation. *Frontiers in Educational Psychology*, *4:*, 994. doi:10.3389/fpsyg.2013.00994

Newtson, D. (1973). Attribution and the unit of perception of ongoing behavior. *Journal of Personality and Social Psychology, 28*, 28-38.

Newtson, D., & Engquist, G. (1976). The perceptual organization of ongoing behavior. *Journal of Experimental Social Psychology*, *12*(5), 436-450. doi:10.1016/0022-1031(76)90076-7

Peirce J.W. (2009). Generating stimuli for neuroscience using PsychoPy. *Frontiers in Neuroinformatics. 2*:10. doi:10.3389/neuro.11.010.2008

Reynolds, J. R., Zacks, J. M., & Braver, T. S. (2007). A computational model of event segmentation from perceptual prediction. *Cognitive Science*, *31*(4), 613-43. doi:10.1080/15326900701399913

Rinck, M., & Weber, U. (2003). Who when where: an experimental test of the event-indexing model. *Memory & Cognition*, *31*(8), 1284–1292.

Schneider, W., Eschman, A., & Zuccolotto, A. (2002). E-Prime user's guide. Pittsburgh: Psychology Software Tools.

Schwan, S., & Ildirar, S. (2010). Watching film for the first time: How adult viewers interpret perceptual discontinuities in film. *Psychological Science*, *21*(7), 970–976. doi:10.1177/0956797610372632

Schwan, S., & Garsoffky, B. (2004). The cognitive representation of filmic event summaries. *Applied Cognitive Psychology*, *18*(1), 37-55. doi:10.1002/acp.940

Schwan, S., & Garsoffky, B. (2008). The role of segmentation for perception and understanding of events. In T. Shipley & J. Zacks (Eds.), *Understanding events: From perception to action* (pp. 391–414). Oxford, UK: Oxford University Press.

Scott-Rich, S., & Taylor, H. A. (2000). Not all narrative shifts function equally. *Memory & Cognition*, *28*(7), 1257–66.

Smith, T. J., & Henderson, J. M. (2008). Edit blindness: The relationship between attention and global change blindness in dynamic scenes. *Journal of Eye Movement Research*, *2*(2), 1–17.

Speer, N. K., & Zacks, J. M. (2005). Temporal changes as event boundaries: Processing and memory consequences of narrative time shifts. *Journal of Memory and Language*, *53*(1), 125-140. doi:10.1016/j.jml.2005.02.009

Swallow, K. M., Zacks, J. M., & Abrams, R. A. (2009). Event boundaries in perception affect memory encoding and updating. *Journal of Experimental Psychology: General*, *138*(2), 236-257. doi:10.1037/a0015631.

Szewczyk, J. M., & Schriefers, H. (2013). Prediction in language comprehension beyond specific words: An ERP study on sentence comprehension in Polish. *Journal of Memory and Language*, *68*(4), 297–314. doi:10.1016/j.jml.2012.12.002

Van Dijk, T.A., & Kintsch, W. (1983). *Strategies of discourse comprehension*. New York: Academic Press.

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

Zacks, J. M., Kumar, S., Abrams, R. A., & Mehta, R. (2009). Using movement and intentions to understand human activity. *Cognition*, *112*(2), 201-16. doi:10.1016/j.cognition.2009.03.007

Zacks, J. M., Kurby, C. A., Eisenberg, M. L., & Haroutunian, N. (2011). Prediction error associated with the perceptual segmentation of naturalistic events. *Journal of Cognitive Neuroscience*, *23*(12), 4057-4066. doi:10.1162/jocn_a_00078

Zacks, J. M., Speer, N. K., & Reynolds, J. R. (2009). Segmentation in reading and film comprehension. *Journal of Experimental Psychology: General*, *138*(2), 307-27. doi:10.1037/a0015305

Zacks, J. M., Speer, N. K., Swallow, K. M., Braver, T. S., & Reynolds, J. R. (2007). Event perception : A mind-brain perspective. *Psychological Bulletin*, *133*(2), 273-293. doi:10.1037/0033-2909.133.2.273

Zacks, J. M., Speer, N. K., Vettel, J. M., & Jacoby, L. L. (2006). Event understanding and memory in healthy aging and dementia of the Alzheimer type. *Psychology and Aging*, *21*(3), 466-82. doi:10.1037/0882-7974.21.3.466

Zacks, J. M., & Tversky, B. (2003). Structuring information interfaces for procedural learning. *Journal of Experimental Psychology: Applied*, *9*(2), 88.

Zwaan, R. A. (1999). Situation models : The mental leap into imagined worlds. *Current Directions in Psychological Science*, *8*, 15-18.

Zwaan, R. A., Langston, M. C., & Graesser, A. C. (1995). The construction of situation models in narrative comprehension: An Event-Indexing Model. *Psychological Science*, *6*(5), 292-297. doi:10.1111/j.1467-9280.1995.tb00513.x

Zwaan, R. A., Magliano, J. P., & Graesser, A. C. (1995). Dimensions of situation model construction in narrative comprehension. *Journal of Experimental Psychology: Learning, Memory and Cognition*, *21*(2), 386-397.

Zwaan, R. A., & van Oostendorp, H. (1993). Do readers construct spatial representations in naturalistic story comprehension? *Discourse Processes*, *16*, 125-143.

Zwaan, R. A., & Radvansky, G. A. (1998). Situation models in language comprehension and memory. *Psychological Bulletin*, *123*(2), 162-85.

Zwaan, R. A., Radvansky, G. A., Hilliard, A. E., & Curiel, J. M. (1998). Constructing multidimensional situation models during reading. *Scientific Studies of Reading*, *2*(3), 199-220.

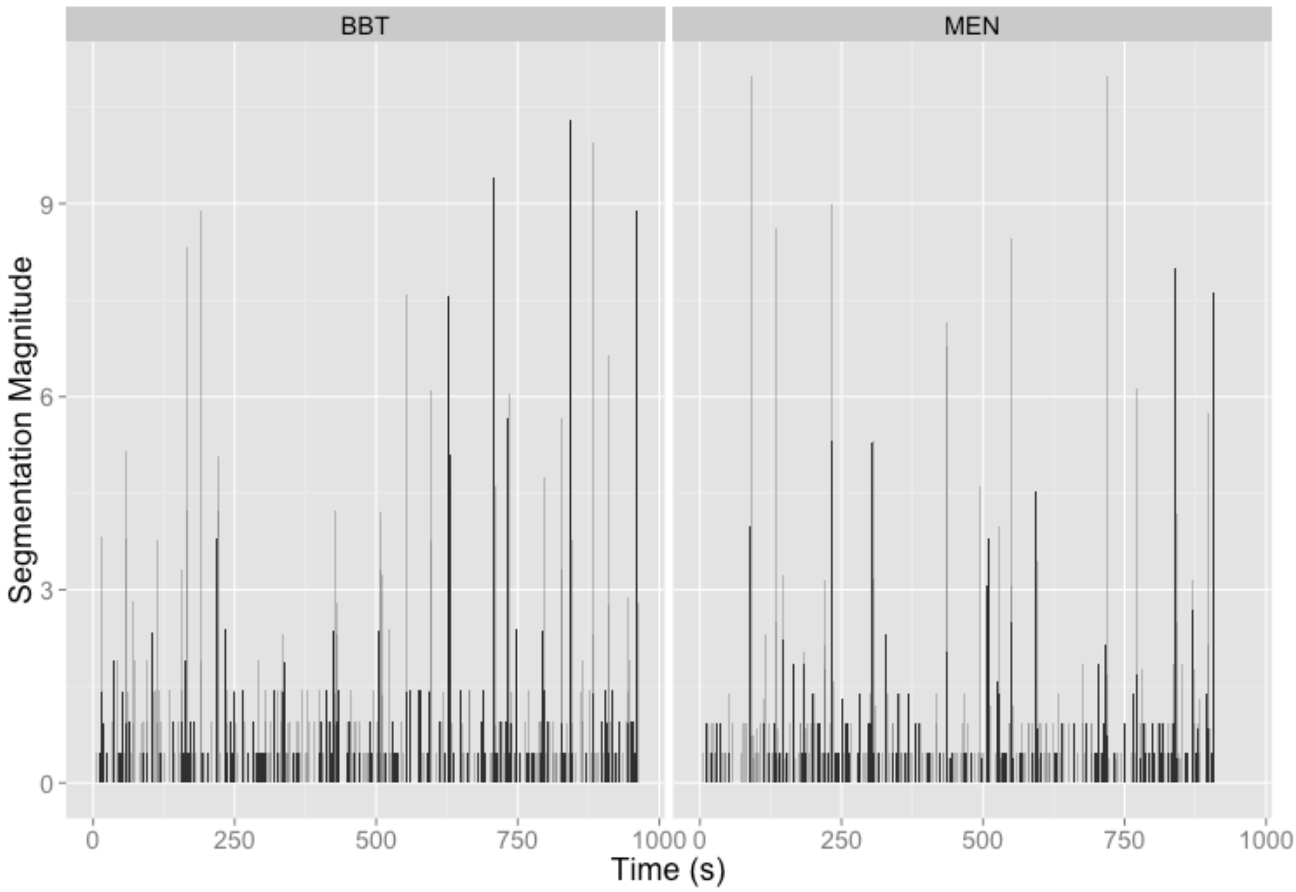

Figure 1. Segmentation magnitude for the two sitcoms.

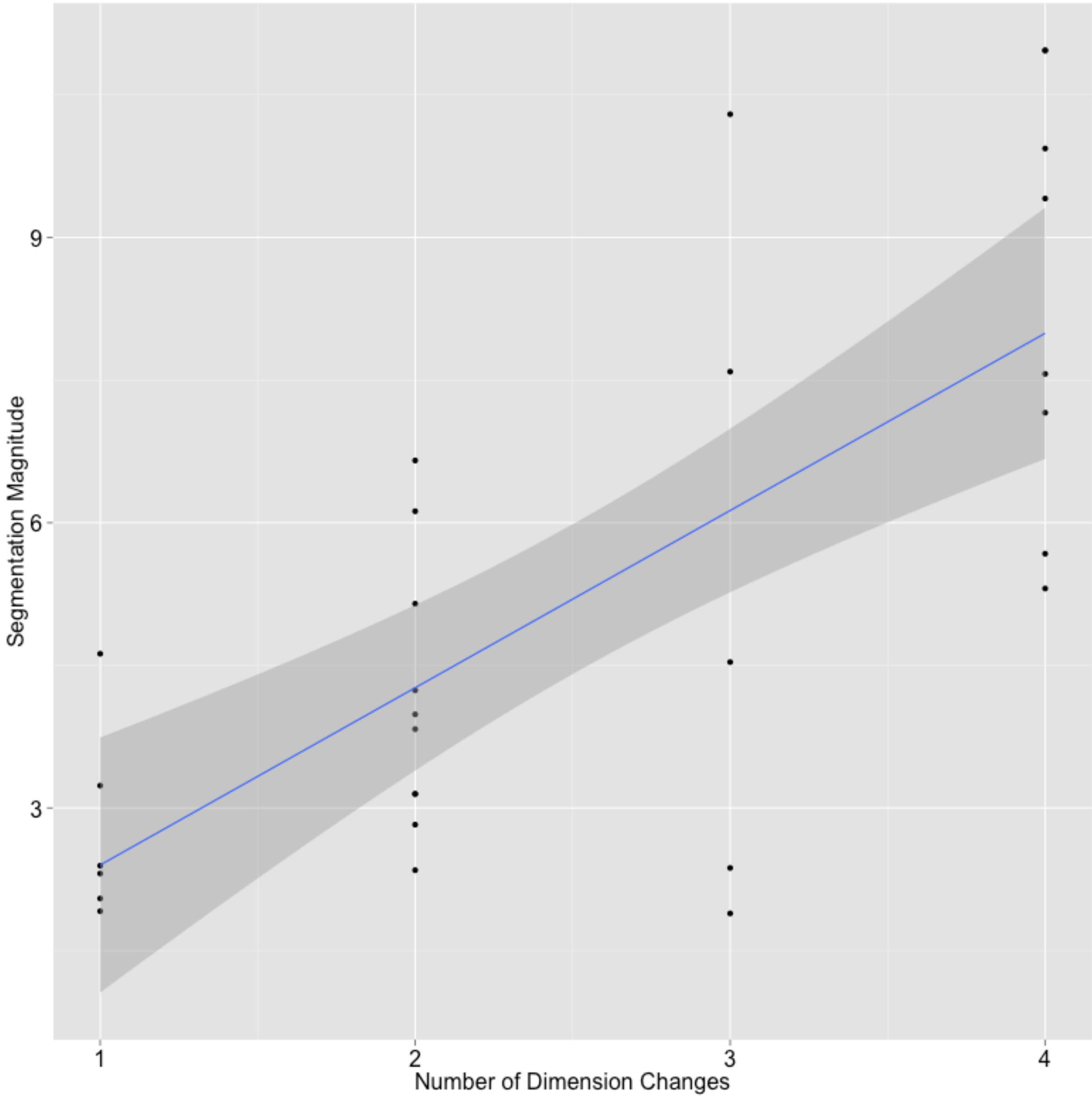

Figure 2: Positive correlation between segmentation magnitude and number of dimension changes at an event boundary.

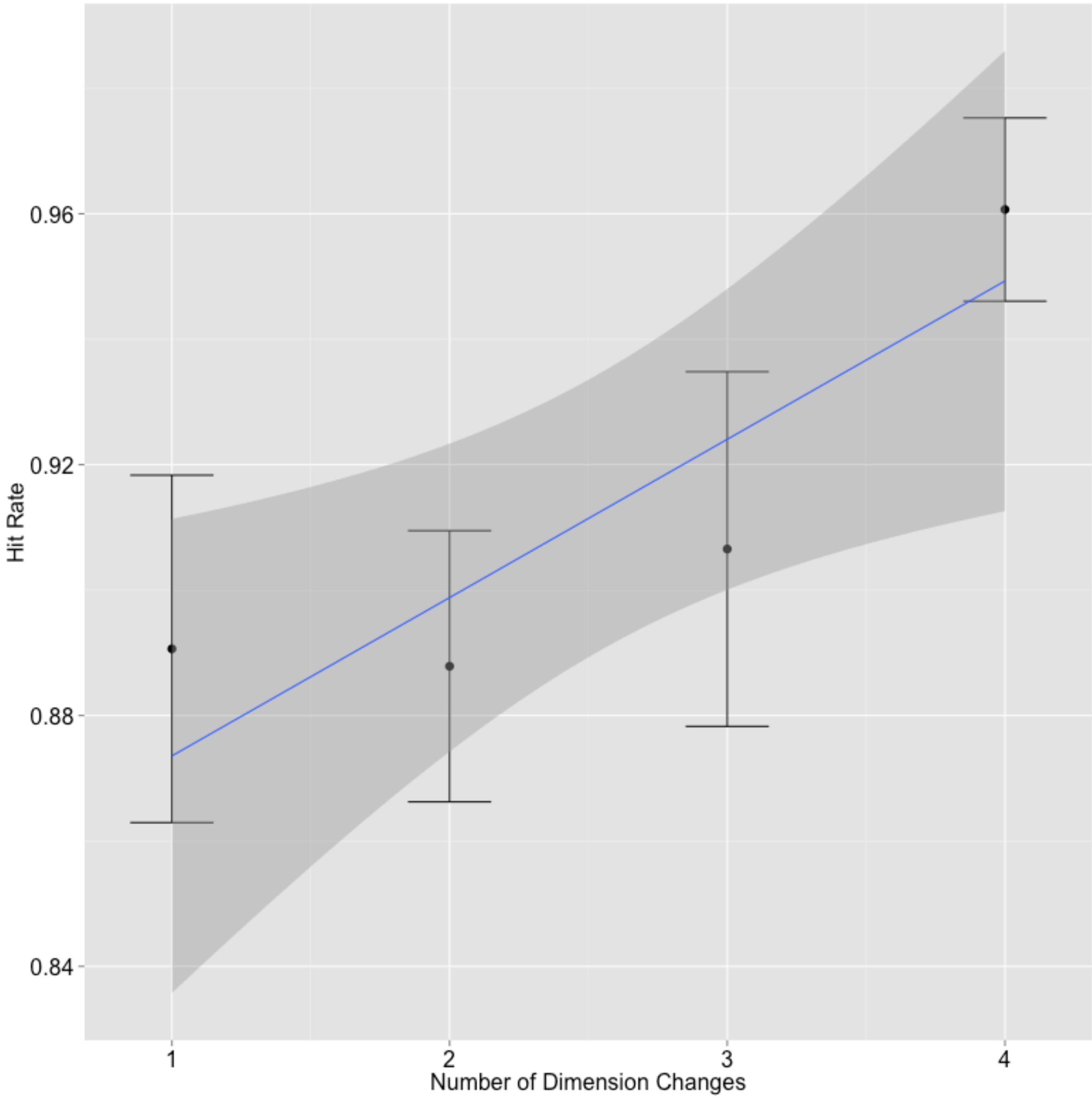

Figure 3: Mean proportion correct scores in the visual recognition test of the memory experiment. Error bars indicate the standard error of the mean.

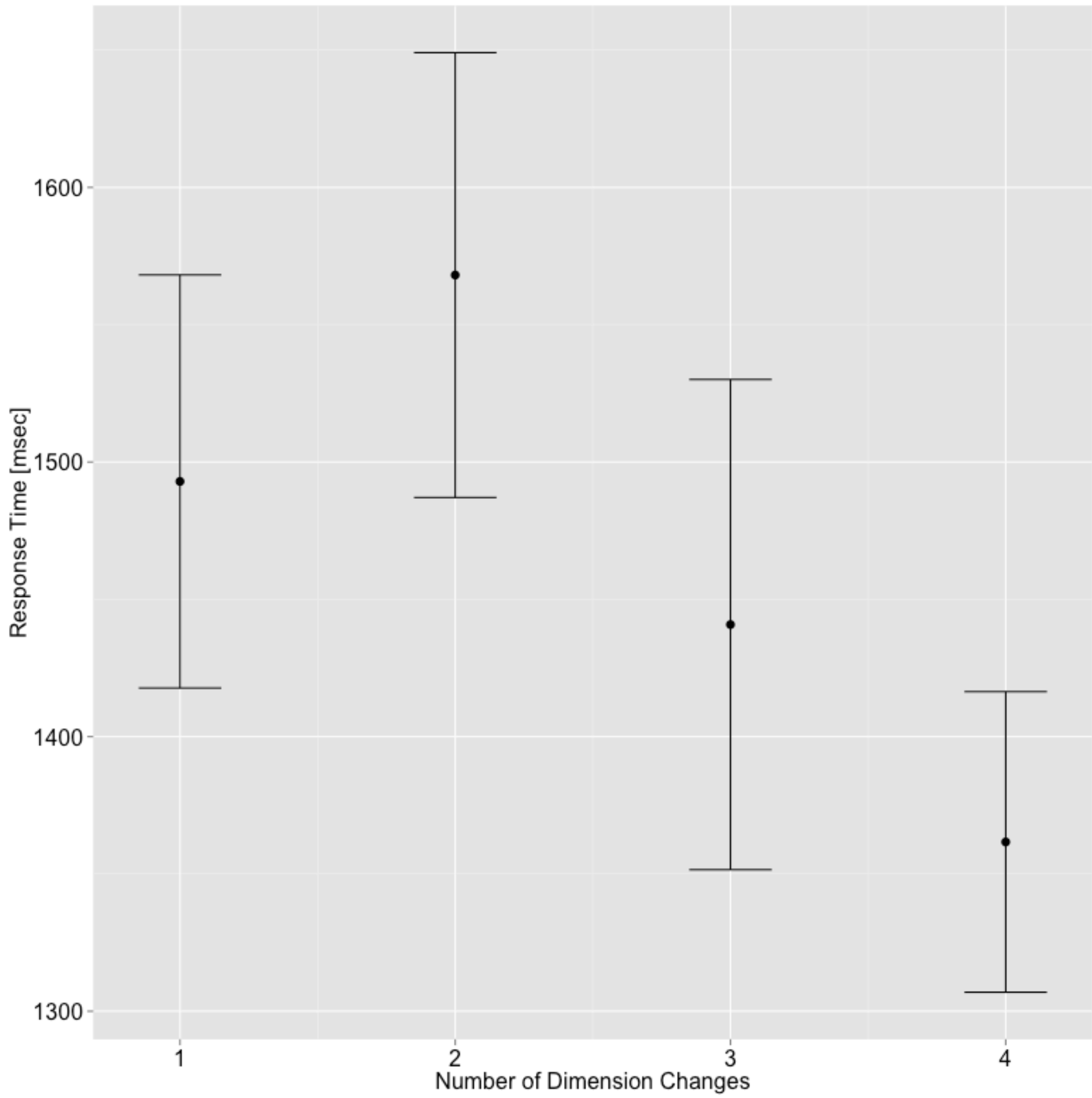

Figure 4: Mean response times of hits in the memory experiment. Error bars represent the standard error of the mean.

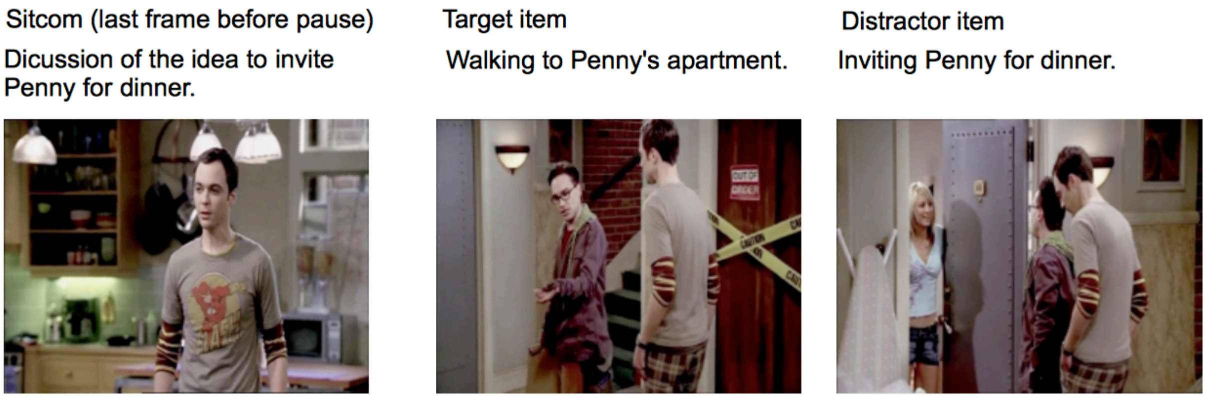

Figure 5. Example of a target-distractor item pair of BBT (Big Bang Theory; Lorre & Cendrowski, 2007) used in the prediction experiment. The sitcom is paused when the two main characters Leonard and Sheldon discuss the idea to invite Polly for dinner. Only Leonard and Sheldon are involved in this discussion. No other character is present. This is 2500 ms before an event boundary. The target item, which was recorded 5000 ms after the pause (2500 ms after the event boundary) depicts Leonard and Sheldon in the hallway walking to Penny's apartment. The distractor item was recorded another 7000 ms later (1000 ms after the next event boundary) and depicts Leonard and Sheldon talking to Penny.

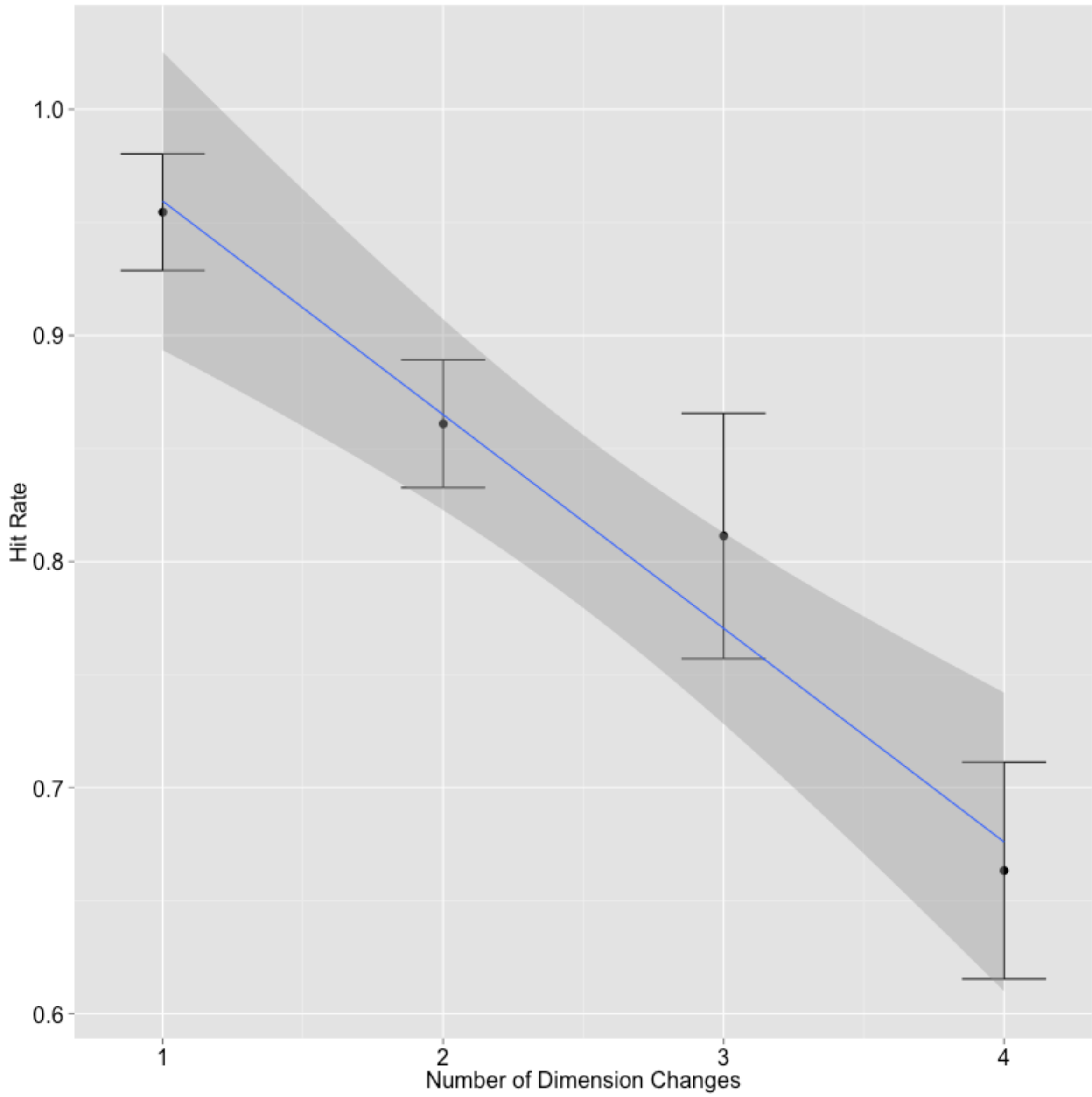

Figure 6. Hit rate of the prediction experiment. Error bars represent the standard error of the mean.

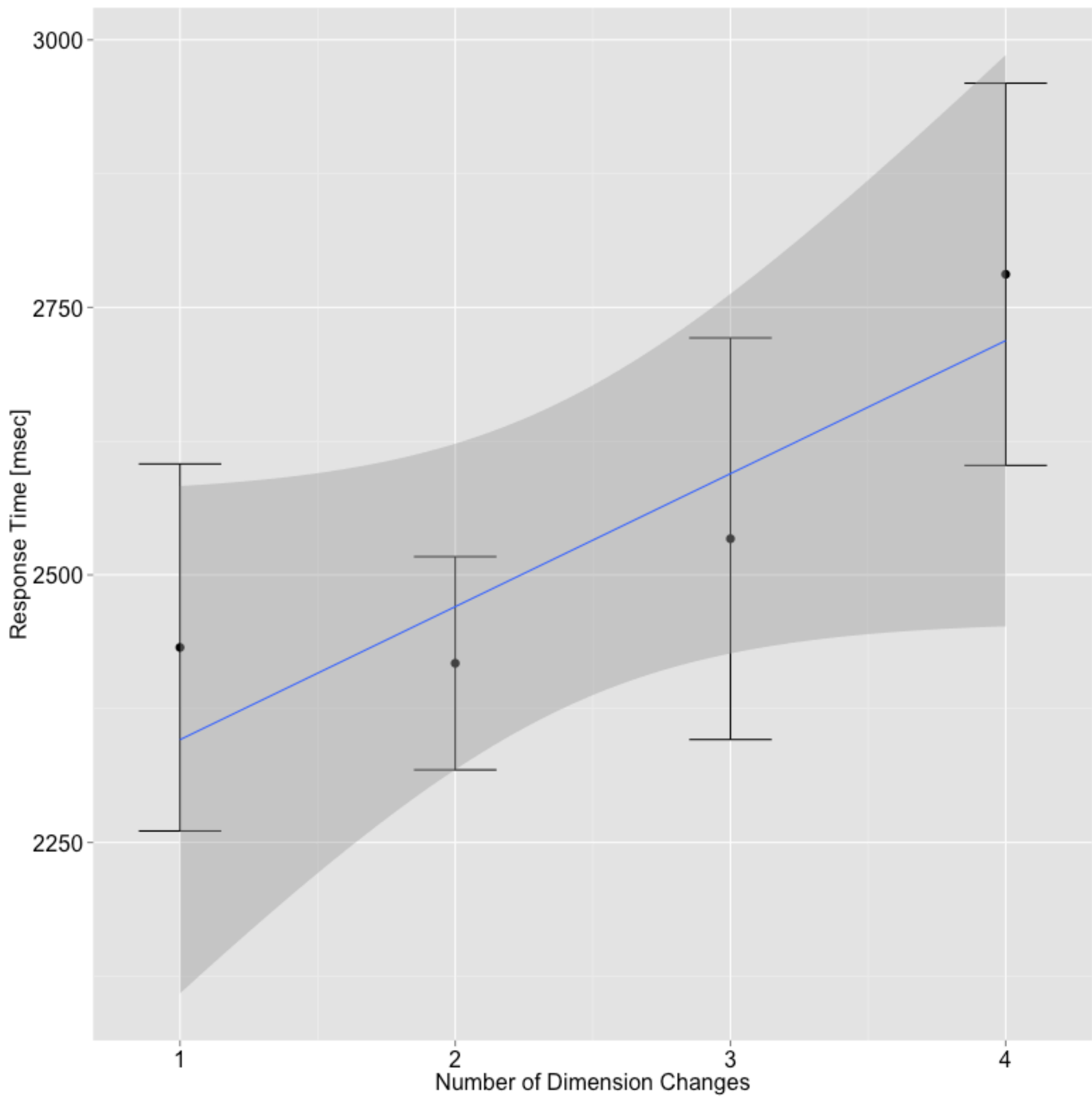

Figure 7. Response times of hits in the prediction experiment. Error bars represent the standard error of the mean.

Table 1. Types of event boundaries and mean segmentation magnitude used in this study (standard deviation in parentheses).

Number of dimension changes	Number boundaries / condition	Segmentation magnitude
1	6	3.08 (0.93)
2	4	4.29 (1.74)
3	4	4.49 (3.24)
4	8	8.42 (2.15)

Table 2. Correlation matrix of the dimension changes at the selected event boundaries.

	Location	Action	Character	Time
Location	1.00	.21	-.05	.76 **
Action		1.00	-.16	.16
Character			1.00	.14
Time				1.00

** $p < .001$

Table 3: Results of the mixed-effects model of the linear lme model of the dependent variable hits.

	Estimate	*SE*	*df*	*t*	*p*
Intercept	0.87	0.03	601	40.91	< .001
Dimension changes	0.03	0.01	601	2.50	.013

Table 4: Results of the intercept model including of the dependent variable response times of hits in the memory experiment.

	Estimate	*SE*	*df*	*t*	*P*
Intercept	1444	86	547	16.68	< .001

Table 5: Results of the lme model for hit rates in the prediction experiment.

	Estimate	*SE*	*df*	*t*	*p*
Intercept	0.96	0.03	334	28.28	< .001
Dimension changes	-0.09	0.02	334	-5.21	< .001

Table 6: Results of the linear lme model of the dependent variable response time of hits in the prediction experiment.

	Estimate	*SE*	*Df*	*t*	*p*
Intercept	2411	165	257	14.59	< .001
Dimension changes	135	60	257	2.26	.025

Appendix A

Film	Event boundary	Time	Temporal change	Character change	Location change	Action change	Number of changes	Cut	Segmentation magnitude	Shot length
BBT	1	00:13,00	No	No	No	Yes	1	Yes	3.83	1.1
	2	00:57,00	No	Yes	No	Yes	2	Yes	5.15	4.3
	3	01:10,00	No	No	Yes	Yes	2	Yes	2.83	4
	4	01:44,00	No	No	Yes	Yes	2	Yes	2.35	7.8
	5	02:43,00	Yes	No	Yes	Yes	3	Yes	1.89	1.9
	6	03:08,00	Yes	Yes	No	No	2	Yes	1.91	2.0
	7	03:54,00	No	No	No	Yes	1	Yes	2.39	1.2
	8	07:05,00	No	Yes	No	Yes	2	Yes	4.24	4.8
	9	09:13,00	No	Yes	Yes	Yes	3	Yes	7.59	1.9
	10	10:28,00	Yes	Yes	Yes	Yes	4	Yes	7.57	19.9
	11	11:48,00	Yes	Yes	Yes	Yes	4	Yes	9.41	3.8
	12	13:14,00	Yes	No	Yes	Yes	3	Yes	2.37	4.5
	13	13:47,00	Yes	Yes	Yes	Yes	4	Yes	5.67	7
	14	14:03,00	Yes	No	Yes	Yes	3	Yes	10.30	18.8
	15	14:41,00	Yes	Yes	Yes	Yes	3	Yes	9.94	1.9
	16	15:09,00	No	Yes	No	Yes	2	Yes	6.65	1.6
MEN	1	01:29,00	Yes	Yes	Yes	Yes	4	Yes	10.97	4.9
	2	02:26,00	No	No	No	Yes	1	Yes	3.24	2.9
	3	03:02,00	No	No	No	Yes	1	Yes	2.05	3.5
	4	03:39,00	No	Yes	No	Yes	2	Yes	3.15	3.5
	5	05:05,00	Yes	Yes	Yes	Yes	4	Yes	5.31	1.8
	6	05:28,00	No	No	No	Yes	1	Yes	2.31	5.2
	7	07:15,00	Yes	Yes	Yes	Yes	4	Yes	7.16	2.9
	8	08:12,00	No	No	No	Yes	1	Yes	4.62	1.0
	9	08:46,00	No	Yes	No	Yes	2	Yes	3.98	3.2

10	09:53,00	No	No	Yes	Yes	2	Yes	4.53	7.1
11	11:57,00	Yes	Yes	Yes	Yes	4	Yes	10.97	3.2
12	12:51,00	No	Yes	No	Yes	2	Yes	6.12	4.7
13	14:29,00	No	Yes	No	Yes	2	Yes	3.15	3.3