CAN ATTENTIONAL PATTERNS PREDICT THE FUTURE? A NOVEL VIEW INTO WHO IS LIKELY TO EXPERIENCE CHANGE BLINDNESS

by

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People witnessing identical streams of information can experience that information very differently. This phenomenon was strikingly documented in a famous psychological experiment: one group of research participants watching a video of a crowded area failed to notice a man in a gorilla suit meander across the room, although another group described the man in the gorilla suit as the most salient aspect of the video. How do we account for such diversity in experience? My research investigates this general question via a new technique: the dwell-time paradigm, in which viewers advance at their own pace through slideshows depicting dynamic events while the time they spend dwelling on each image is measured. We hypothesized that patterns of dwelling across time would clarify which aspects of events viewers prioritized in their processing, and thus we would be able to predict – well in advance -- who would subsequently report salient features of interest. Our findings provided compelling evidence that dwell-time patterns do in fact provide predictive information about the probability that a viewer will be subject to change blindness. This finding has far-reaching implications. Specifically, it will be possible to utilize dwell-time patterns across a range of situations where monitoring the focus and adequacy of people's attention is crucial. For example, applications could include a) refinements to diagnosis in those with attentional impairments, and b) the creation of systems that alert people when their attentional patterns have become suboptimal for an essential task, such as drivers, train operators, and pilots.

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Introduction

Texting while walking down a busy sidewalk is a dangerous endeavor. While it is possible to avoid obstructions and text at the same time, it also puts one at risk of grave mishaps, such as straying off a sidewalk into the path of an oncoming car. But why does this occur? If the human brain is truly as finely tuned as we believe, why do changes in the background so often go unnoticed, and why do some people notice changes that others miss completely? Change blindness is arguably one of the most well-known psychological phenomena in the field of cognitive psychology. Often defined as the inability to notice changes to a visual scene, change blindness can have negative implications for everyday functioning. Air traffic control failures, problems with eyewitness testimony, car accidents, and even the dangers of texting while walking have all been attributed in part to change blindness (*Change Blindness Is How We Miss the Big Changes Around Us*, n.d.). With significant real-world implications, it is important to understand change blindness in as much depth as possible. Specifically, it is important to understand when and why change blindness may occur. In the present thesis, I take advantage of a relatively new methodology – the dwell-time paradigm – to assist in predicting when an individual is likely to experience change blindness before the error occurs.

Change Blindness

Change blindness studies date back to the 1980s, but the popularity of change blindness research remained relatively low until the phenomenon garnered attention in the 1990s (Simons & Rensink, 2005). At this time, researchers gained access to new technology to study the phenomenon. The emergence of recordings and videos used to study change blindness sparked the beginning of modern research and public interest in change blindness (O'Regan et al., 1999).

Specifically, two studies performed by Simons and colleagues can be largely credited for the popularization of change blindness. One study consisted of a researcher switching places with a second researcher during a conversation with a research participant. Strikingly, participants failed to notice when the researcher they had been speaking to was replaced by another person (Simons & Levin, 1998). The second popularized study demonstrated how individuals who are preoccupied with a task fail to notice what would seem to be extremely obvious changes in their surroundings. Participants watched a video in which, among other things, a person dressed in a gorilla suit passed through a crowded room (Simons & Chabris, 1999). In this video, some participants were tasked with tracking the number of times a ball passed between people in the room; others were simply asked to watch the video. Those who merely watched tended to notice, and report, the presence of the person in the gorilla suit, whereas those who'd been instructed to count ball passes typically failed to do so. The striking results in these studies fascinated the public and scientists alike, creating two of the most well-known psychological studies to date. Popular media organizations, including NOVA, have discussed the phenomenon in great detail (NOVA PBS Official, 2011).

Definitionally, change blindness is known as a failure to notice changes in an environment (Simons & Chabris, 1999). Under the right processing circumstances, the unnoticed change can be quite striking, leaving many surprised over the lack of attentiveness our brains are capable of (Simons & Rensink, 2005). Change blindness bears close relationship to another kind of visual awareness failure, known as inattentional blindness, which is a failure to notice something that was unexpected (Jensen et al., 2011). These two phenomena often operate together to create a lack of awareness to apparently salient stimuli. In the present study, both change blindness and inattentive blindness are technically operative; as a shorthand, we will simply use the term "change blindness" to refer to the failures of visual awareness under investigation.

The extent to which change blindness occurs is well researched. Recent work shows that change blindness not only happens in daily experiences, but that the phenomenon occurs more frequently than people tend to expect (Simons & Rensink, 2005). Further, people overestimate their perceptual abilities by believing they can detect changes at a higher rate than their actual ability. This "change blindness blindness," as it is known, helps to explain why people are so fascinated with the phenomenon (Levin et al., 2002).

Change blindness is directly related to attention. When attempting to detect changes in one's environment, attention must be utilized to identify said changes. Extensive investigation indicates that changes can only be detected in areas that are actively attended (Rensink, 2002). Requiring participants to pay greater attention to specific events in an environment creates increased blindness to change in other areas. This is especially true when given a complex task to follow (Simons & Chabris, 1999). The more difficult the task, the more attentional resources are used, leading to reduced change detection for unattended content.

Failures of visual awareness such as change blindness apply cross-culturally. At the same time, culture does appear to have some impact on the degree to which change blindness occurs. For example, Masuda & Nisbett (2006) found that, relative to Western research participants, participants living in China were more likely to pay attention to events in the periphery of their given environment. Thus, Chinese participants were less likely to experience change blindness to such peripheral events. Conversely, Western participants paid greater attention to centralized objects than Eastern individuals, and therefore experienced change blindness to centralized objects to a lesser degree.

Clearly, change blindness is a well-studied psychological phenomenon that has fascinated both the public and researchers alike for the last half-century. Change-blindness appears to be a highly replicable phenomenon that has been observed for many different stimuli, situations, and even cross-culturally (Masuda & Nisbett, 2006; Simons & Rensink, 2005). However, relatively little is known about attentional patterns underlying change-blindness as events dynamically unfold in real time. That is, to our knowledge, no investigation has yet explored specific patterns of attention as events are experienced that might predict subsequent self-reported change blindness. My thesis addresses this gap in current understanding. To do so, I have utilized a relatively new technique for measuring observers' attentional patterns as an events stream passes: the dwell-time paradigm. Below I first describe the dwell-time methodology, and then explain how I used it to examine attentional patterns associated with change blindness.

The Dwell-Time Paradigm

Change blindness occurs as an individual experiences a given event. It is in the processing of this event where the potential for a change blindness error may or may not occur. The processing of event streams may seem like a complex and highly diversified process, but research shows that the human brain transforms sensory events into consistently structured mental representations that support memory, problem-solving, and even predict how a given event stream will unfold (Kosie & Baldwin, 2019). Understanding more about how sensory events are processed is an important goal that has the potential to lead to many discoveries. The research presented in this study aimed to use a new methodology for studying attention as events unfold to deepen current understanding of event processing, and potentially identify a predictive measure of change blindness.

At its most basic level, the processing of event streams involves parsing a single event into multiple, smaller, events. While there are theoretically an unending number of ways to divide a single activity into multiple parts, people display significant consistency in their interpretations of where a given event, or parts of a singular event, begin and end (Baldwin & Baird, 1999; Newtson, 1973; Zacks et al., 2001). This consistency appears to reflect agreement in identifying event boundaries – where one event ends and the next begins – as well as in organizing the resulting event representations hierarchically in a partonomic structure. For example, within sequences of human action, some event boundaries demarcate large-scale or "coarse-grain" events, such as execution of large-scale tasks. Each coarse-grain level event, however, contains within it multiple smaller-scale events; "fine-grain" boundaries demarcate the transition between the end of one such fine-grain event and the beginning of the next (Baird & Baldwin, 2001; Zacks & Swallow, 2007). That is, coarse grain boundaries are associated with larger-scale events and fine-grain boundaries with smaller-scale transitions. For example, take a person tying their shoes. Completion of tying one shoe and moving onto the next is an example of a coarse-grain boundary, whereas the act of pulling shoelaces tight as one executes tying of one particular shoe is a more fine-grain level event boundary.

Organized hierarchically, event boundaries are essential in the successful processing of an event. Studies show that accurate identification of event boundaries by an observer positively predicts better recall performance, better sequential ordering performance, and better memory for action enactment (Bailey et al., 2013; Zacks et al., 2006; Zacks & Swallow, 2007). Further, when presented with either still-frame images of event boundaries, or non-boundary still-frames, observers found non-boundary still frames more difficult to interpret and harder to memorize (Newtson & Engquist, 1976; Schwan et al., 2000; Schwan & Garsoffky, 2004). These studies, combined with other sources of evidence such as fMRI and reaction time tasks suggest that processing action through organizing event boundaries is spontaneous and automatic (Baldwin & Pederson, 2016; Huff et al., 2012; Saylor & Baldwin, 2004; Zacks et al., 2001).

A recently developed research methodology known as “dwell-time” has provided additional insights into how attentional processes work during event processing. First developed by Hard and colleagues (Hard, Recchia, & Tversky, 2011), the dwell time methodology measures viewers’ attention as viewers advance through an event stream in slideshow form at their own pace. Slideshows are created by extracting images from video-recorded events at a regular increment, such as once every 500ms, and viewers advance through the slideshow at their own pace by clicking a computer mouse or pressing a spacebar. The latency between mouse clicks provides an index of the length of time viewers spend looking at each slide, thereby providing information about the deployment of attention as event processing is underway.

Through this methodology, Hard and colleagues discovered predictable patterns the way attention is deployed during event processing. One such pattern is known as the boundary advantage, referring to a common trend for longer dwelling to slides which contain boundaries rather than non-boundary (within) slides. A second trend is known as the hierarchical advantage. This term refers to the trend in attentional patterns for individuals to dwell longer at coarse-grain than fine-grain boundaries. These trends directly suggest preferential attention to boundaries, and further indicate that boundaries are important for the proper comprehension of unfolding action. As the field of dwell-time research continues to develop, multiple studies show evidence of the boundary and hierarchical advantages with both fine motor activities like sleight-of-hand tricks and gross-motor activities like unloading groceries (Hard et al., 2019; Kosie & Baldwin, 2019; Sage & Baldwin, 2014). Even children as young as preschool-age display these patterns in their dwelling as they advance through slideshow sequences of diverse events (Meyer, Baldwin, & Sage, 2011; Kosie & Baldwin, 2021).

Hard et. al.'s 2011 study also demonstrated that scrambled slideshows do not replicate the boundary and hierarchical advantage effect to as great a degree as compared to an unscrambled slideshow (Hard et al., 2011). This indicates that dwell-time patterns genuinely reflect processes underlying individuals' active efforts to make sense of unfolding events during slideshow viewing, and the patterned nature of dwell times allow for predictions to be made regarding downstream cognitive processes. For example, dwell times are predictive of later recall for a given event stream (Hard et al., 2011). The ability of dwell time to predict future recall suggests that dwell time reflects an individual's expenditure of attentional resources as they view an event, with longer dwell times indicating more attentional resources being used at a given moment. The ability of dwell time research to track attention at specific moments during dynamic action makes it a powerful tool to gather detailed information on how attention is deployed to make sense of events as they stream past.

Event Segmentation Theory (EST) may help to explain why individuals process continual event streams in such predictable ways (Kurby & Zacks, 2008). EST proposes that continual events are segmented to make the prediction of upcoming events easier. Event segmentation theory postulates that as viewers observe an event, they hold preconceived schemas about how the event will unfold. When the given event is consistent to the individual's schema, the event is highly predictable. EST posits that event boundaries represent regions of an event stream with low predictability, that also convey high levels of information. Kurby and Zacks theorize that these information-rich areas are more likely to not fit with an individual's preconceived schema. This makes these boundaries more surprising and require more attention (Kurby & Zacks, 2008). According to Kosie and Baldwin (2019, Baldwin & Kosie, 2020), EST should be modified to suggest that observers not only pause at event boundaries in response to surprisal, but instead also proactively direct attention to boundaries because they are predictably informative regions within unfolding activity. That is, projecting additional attentional resources into regions that are information rich – in the sense that they are predictably unpredictable -- allows for greater ease of event processing (Baldwin & Kosie, 2020; Kosie & Baldwin, 2019).

Event segmentation theory can easily be understood through the example of an event in which two people are passing a ball back and forth. As an individual watches this event unfold, the process of passing a ball back and forth could easily be broken down into different segments. When observers watch such an event and are asked to identify units of action within the stream, they tend to display high levels of agreement, identifying, for example, the span between one actor launching a ball into the air and the ball being caught by the other actor as an action unit or segment. In this example, the region within the event that the ball is caught is a boundary between one action segment (the toss) and the next. It is at such boundaries that unpredictability is high. For example, when the ball has been caught, it is suddenly uncertain what will happen next. Will the catcher launch a return toss to the same actor? Or confiscate the ball and run away with it? Or bounce it on the ground? Or toss it to someone else? Or drop kick it into the distance? And so on. In contrast, predictability mid-segment – once the next action has been initiated – tends to be considerably higher. If, for example, the actor initiates a return toss back to the original tosser, then it is fairly predictable that the ball will arc through the air in that person's direction at a predictable velocity. Where uncertainty arises again is when the next event boundary approaches: will the original tosser choose to, and succeed in, catching the ball? And if so, what will the original tosser opt to do next? Again, it is at event boundaries that predictability is low, whereas within-event regions tend to exhibit relatively higher predictability. EST posits that it is those areas of high unpredictability that elicit more attention, and thus receive extended dwelling in the dwell-time paradigm.

Recent dwell-time research showcases how attentional patterns change as observers gain increasing familiarity with, and understanding of, novel event streams (Baldwin & Kosie, 2021). There appear to be two key drivers of attention that are readily observable in dwell-time patterns: one is called a “pro-active” mechanism. The pro-active mechanism depends on prior knowledge of predictability within event streams. Given knowledge of predictability, viewers will tend to proactively direct more attention to regions within unfolding experience at which predictability is low (i.e., event boundaries). The other driver is a “reactive” mechanism that responds reactively with enhanced attention any time something quite novel or expectation-violating occurs within streaming experience; this is the “surprisal” process that has been highlighted in EST.

Interaction Between Change Blindness and Dwell Time

Clearly, dwell times are fully capable of indexing how an observer processes an unpredictable event, but little research has been performed on how attentional patterns respond to unexpected and potentially unnoticed changes in an event stream. The change blindness phenomenon provides an avenue to explore this under researched area of dwell time. For the research performed in this study, we conducted two experiments to come to conclusions about how dwell times index unseen events.

How might we expect dwell times to change in the presence of unpredictable stimuli? An essential element to change blindness errors is the unexpected nature of the change, often occurring through the presentation of novel stimuli into an event stream, such as a gorilla-suited person passing through a crowded gym. The reactive mechanism mentioned above would account for individuals responding with attention to the unexpected event. If they reactively detected the unusual event, they would be expected to dwell on it. However, to the extent that individuals are deploying extensive attentional resources proactively to achieve a given task – such as counting ball passes among individuals in the crowd – their ability to respond reactively to the unexpected change would be diminished. Thus individual differences in how powerfully pro-active dwelling patterns are displayed, such as boundary and hierarchical advantages, should predict the likelihood that unexpected changes will be detected.

To test these speculations, we undertook two studies. In the first study, we aimed to replicate existing change blindness findings utilizing new event sequences displayed in a slideshow format (as opposed to video format, as is typical in the change blindness literature). As previously observed in earlier studies of change blindness, this experiment tested for replication of change blindness with the slideshows we created. In the second study, we measured dwell times while participants advanced at their own pace through the slideshows for which Study 1 had demonstrated change blindness. We hypothesized that patterns of dwelling across time would clarify which aspects of events viewers were prioritizing in their processing, and thus we would be able to predict – well in advance -- who would subsequently report detection of unexpected changes. More specifically, we predicted that a) task instructions to count events within the slideshows would be associated with an increase in dwell times to boundaries relevant to the count, b) the higher the level of dwelling to count boundaries, the lower the level of subsequently reported change detection, and c) the lower the level of dwelling to slides associated with unexpected changes, the lower the level of subsequent report of change detection.

STUDY 1

Method

Participants

A grand total of 552 subjects recruited from the University of Oregon participated in Experiment 1. This experiment was divided into two different conditions: 225 participated in the video condition, and 227 participated in the slideshow condition. Both conditions' protocol was approved prior to research by the University of Oregon's Office of Research Compliance.

74 participant's data were removed from the video condition as they did not complete the study. The remaining 154 participants who completed participation received credit for their time. Of the 154 participants (M_{age} = 19.6, SD = 2.44), 79.9% were female. The racial demographics of those in the video condition was as follows: 71.9% white, 13.1% Asian, 3.3% American Indian or Alaska Native, 3.3% Black or African American. And 8.5% identified as other. Participants were only allowed to mark one category, with one participant choosing not to respond.

In the slideshow condition, 64 participant's data were removed as they did not complete the survey. Of the 163 that did complete the study (M_{age} = 19.3, SD = 1.60), 74.2% were female. The racial demographics were as follows: 77.9% white, 8.0% Asian, 3.1% Black or African American, 1.8% native Hawaiian or Pacific Islander, and 8.0% other, with 2 participants declining to provide their information.

Materials

Stimulus Creation

Experiment 1 of this study used three videos, and three slideshows over the course of research. The videos used in this study were selected from a list of existing videos online that researchers believed potentially displayed the change blindness phenomenon. The three change blindness videos that were specifically selected for this study were chosen for their short durations and unique presentation of the change blindness phenomenon. As it was important participants in this study not be familiar with the videos prior to viewing, all three of the videos selected for the study were not popular online. They were also markedly different from each other. One video, referred to as the Ball video, displayed two cartoon figures passing a ball back and forth. Another video (called the Card video) displayed a woman flipping up individual cards from a deck and presenting them to viewers. Finally, a third video (called the Cup video) displayed two men seated at a table passing cups back and forth between each other as they shuffled around a ball they had hidden under one of the cups. In each video, at least one unexpected background change took place that observers might miss.

Following the selection of appropriate videos, each video was then turned into a slideshow that maintained consistency with prior research. In the dwell time paradigm, slideshows are created by extracting a still frame at consistent intervals from a video depicting unfolding action (Hard et al., 2011; Meyer et al., 2011). Slideshows for this experiment were created by extracting one frame from every half second of each video.

Procedure

Experiment 1 consisted of two different Qualtrics surveys that were made available to students at the University of Oregon. Each of these surveys aimed to replicate previous research, while confirming the feasibility of experiment 2. One survey aimed to identify if the videos selected for this experiment contained the change blindness phenomenon in video form. The second also aimed to replicate change blindness findings, but in a slideshow format. Participants used a computer to participate in the online surveys created for this research.

Participants were randomly assigned to respond to just one of the two surveys. For both surveys, following a consent agreement and demographics page, participants were randomly assigned into one of three conditions (referred to as the easy, medium, or hard condition). Participants in each condition were instructed to watch all three action sequences, with observers in the medium and hard condition also tasked with keeping a mental count of various activities occurring on screen while the sequence unfolded. In the Easy condition, participants were simply asked to watch the events in the sequence. In the Medium condition, participants were asked to note and/or count the number of times a particular type of event occurred: passes of the ball in the Ball event, displays of a red card in the Card event, and whether the man in the gray shirt's right hand touched the same color cup at the beginning and end of the video in the Cup event. In the Hard condition, participants were asked to count the number of times that two event types occurred: both ball and car passes in the Ball event, displays of both red and black cards in the Card event, and in the Cup event both a) note whether the man in the gray shirt's right hand touched the same color cup at the beginning and end of the video, and b) count the number of times the man in the gray shirt touched a cup with his left hand.

For each condition, participants were asked a series of questions following their viewing of each action sequence. Regardless of assigned difficulty, the questions that followed each video were identical. All participants, regardless of condition, were asked to report a count of the first series of event types (i.e., ball passes in the Ball event, red card displays in the Card event, and whether the man in the gray shirt's right hand touched the same color cup at the beginning and end of the video for the Cup event). Following previous research in the field, participants were asked if they noticed any unusual events, any changes in the background, and finally were asked to report any changes they may have seen through a recognition memory question which contained an equal number of correct answers and foils. Following all three action sequences and questions, participants completed an ADHD questionnaire (which is not analyzed in this thesis) and were debriefed on the study.

Measures

Change Detection

We asked a series of questions that increased in specificity to assess whether observers had noticed the unusual event. After advancing through a given event sequence, participants were provided with a series of three questions relating to the unexpected changes that had occurred within the event sequence. Following trends appearing in previous literature, participants were first asked two general questions about the video they had seen (Simons & Chabris, 1999). The first question asked, "While you were counting, did you notice anything interesting or unusual," with the second question asking, "Did you notice any changes to the background while you were counting." These two questions are self-report measures of change blindness, and regardless of their answers, participants were then asked to respond to a third question that asked them to select any changes they had noticed. This question was a detection accuracy measure and consisted of a multiple-choice question that contained an equal number of foils and correct change blindness occurrences in the event sequence. Participants answered these questions after viewing each event sequence, regardless of which level of task difficulty they were assigned.

Count Performance

Prior to answering any questions relating to change blindness, participants were first instructed to immediately provide their counts they had been instructed to track. These counts served to verify participants had followed instructions. Participants in all three conditions provided their best estimate of each count, and then responded to a confidence question that asked observers to rate their confidence of the estimate from "Not at all confident" to "Very confident." These questions were taken from previous research in the field (Simons & Chabris, 1999).

Design

Study 1 included two between-subjects variables: Format (video versus slideshow) and Condition (Easy, Medium, Hard). As well, it included a repeated measures variable of Event (Ball, Card, Cup). As well, participants in all conditions provided answers to a series of three change-detection questions for each event, as well as answers to questions about their best estimate of the first series count and their level of confidence about their estimated count.

Results

Replicating Change Blindness

One main objective of the first study was to test for replication of change blindness in the new set of video stimuli we selected from the internet, as well as in slideshow versions of those videos. To examine these questions, we conducted a 3 (Condition: Easy, Medium, Hard) by 2 (Format: Video vs. Slideshow) by 3 (Event: Ball, Card, Cup) mixed-design multivariate analysis of variance (MANOVA) that included three dependent measures (Proportion Correct, UnusualID, BackgroundID).

Regarding the two between-subject variables, the MANOVA revealed significant main effects of Condition, $F(6, 608) = 7.9$, $p = .000$, partial eta-squared = .072, and Format, $F(3, 303) = 7.68$, $p = .000$, partial eta-squared = .071, but no significant interaction between Condition and Format. As predicted in regard to the Condition variable (see Figure 1), on all dependent measures change detection rates were higher in the Easy condition relative to both other conditions, as well as in the Medium condition relative to the Hard condition. Regarding the main effect of Format, Figure 2 illustrates that change detection rates were significantly higher in the slideshow relative to the video format across all three dependent measures.

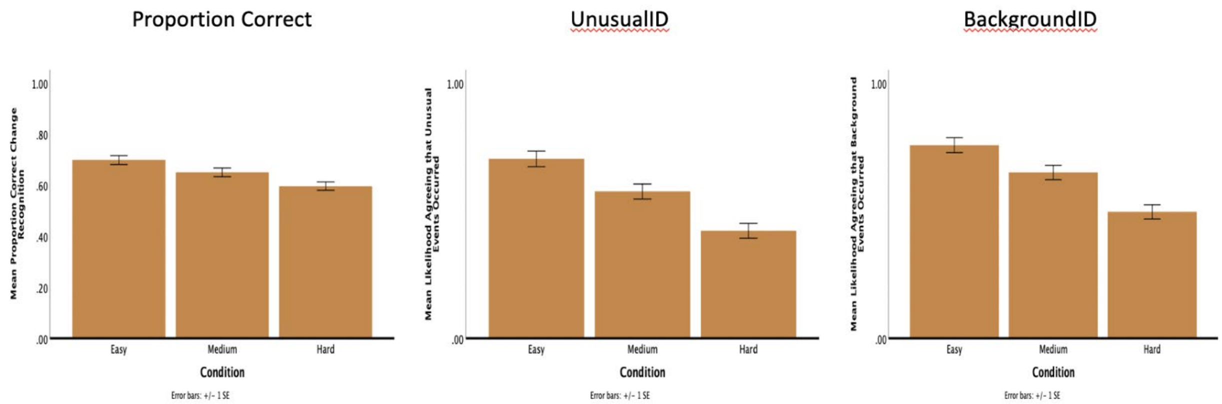

Figure 1: Participants' responses in the Easy, Medium, and Hard conditions to the change recognition, unusual events, and background events questions

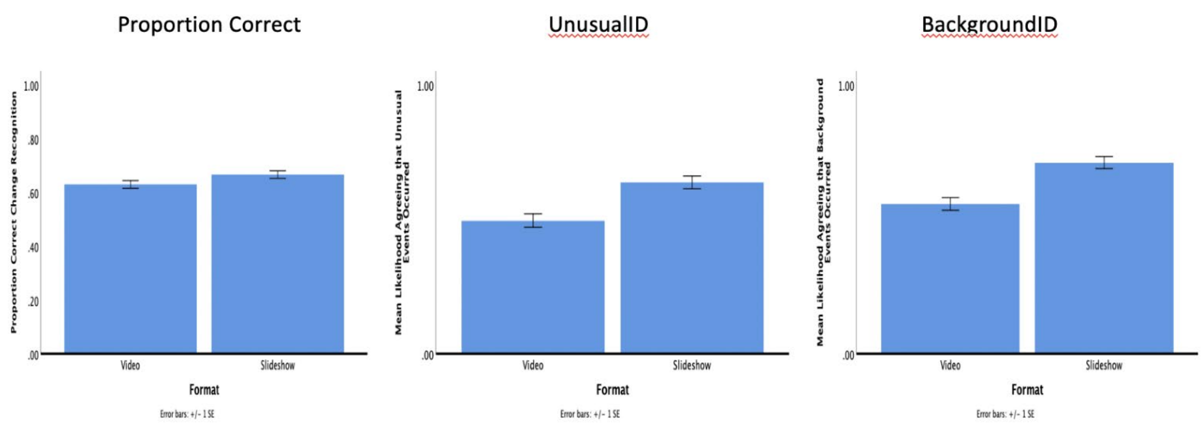

Figure 2: Participants' responses after viewing Video versus Slideshows to the change recognition, unusual events, and background events questions

With respect to the within-subjects Event variable, the MANOVA also revealed a significant main effect, $F(6, 300) = 18.28$, $p = .000$, partial eta-squared = .268, with change detection on all three dependent measures displaying omnibus significant differences across the three events. Univariate analyses confirmed that change detection was significantly higher for the Cup event than the other two events for all three dependent measures, whereas change detection for the Card event significantly exceeded that for the Ball event with the UnusualID and BackgroundID measures (but not the Proportion Correct measure) (see Figure 3).

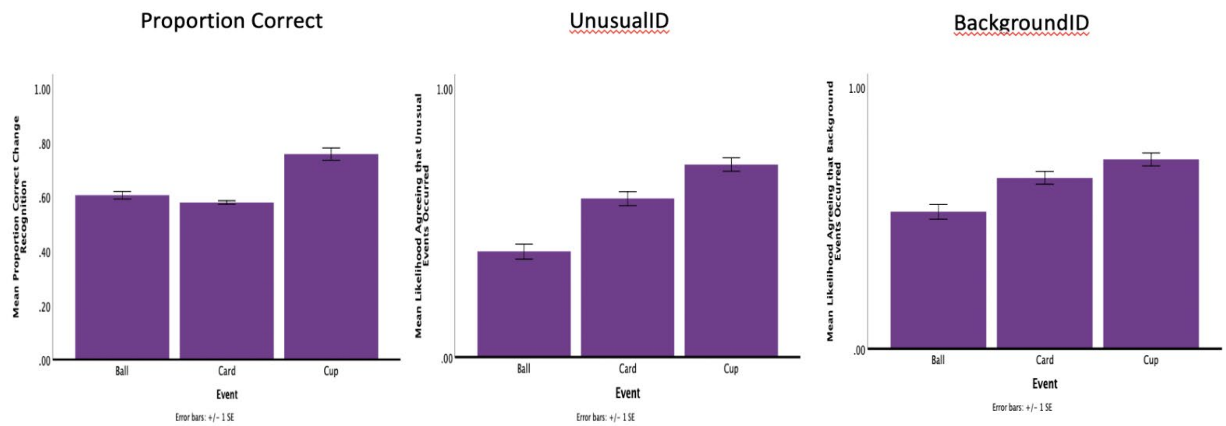

Figure 3: Participants' responses in relation to the Ball, Card, and Cup events to the change recognition, unusual events, and background events questions

The interpretation of the observed main effects of Condition, Format, and Event were rendered somewhat more complex in light of two significant 2-way interactions that emerged in the MANOVA involving the Event variable: 1) Event by Condition, $F(12, 602) = 2.42$, $p = .004$ partial eta-squared .046, and 2) Event by Format, $F(6, 300) = 2.64$, $p = .061$, partial eta-squared = .050. These interactions are illustrated in Figures 4 and 5, respectively. Note that the interactions are displayed only for the dependent measures on which they were statistically significant.

Univariate analyses indicated that the Event by Condition interaction was statistically significant for both the UnusualID and BackgroundID measures, F's(4,610) > 4.66, p's < .001, partial eta-squared's > .03, but not the Proportion Correct measure. Simple-effects analyses to discover the locus of the two significant interactions indicated that change detection rates were significantly higher in the Easy than the Hard conditions across all three dependent measures.

However, significantly higher change detection rates for the UnusualID and BackgroundID measures in the Easy versus Medium conditions, and in the Medium versus Hard conditions, depended on the particular event (Ball, Card, or Cup) at issue. Specifically, for both of the two dependent measures, statistically significant differences between all three conditions emerged for the Card event, whereas Easy and Medium conditions did not differ for the Ball event, and Medium and Hard conditions did not differ for the Cup event.

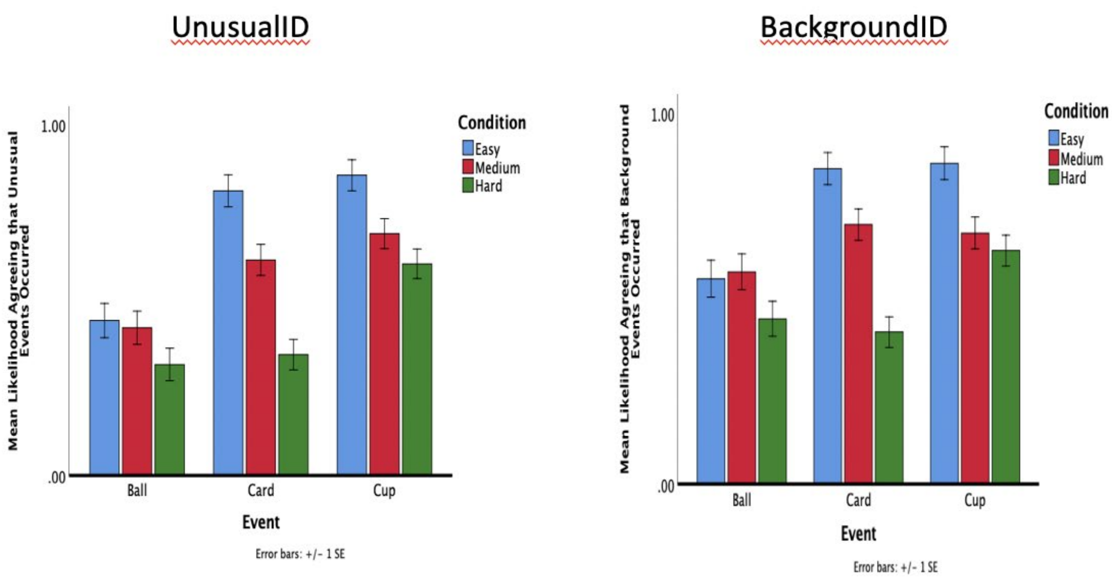

Figure 4: Participants' responses to the unusual and background events questions for the Ball, Card, and Cup events in relation to the Easy, Medium, and Hard conditions

The Event by Format interaction was statistically significant only for the Proportion Correct measure, $F(2,610) = 2.4$, $p = .034$ (see Figure 5). Follow-up analyses exploring the Event by Format interaction with respect to the Proportion Correct measure indicated that change detection rates were higher for the Slideshow than the Video format with the Card and Cup events, but not the Ball event.

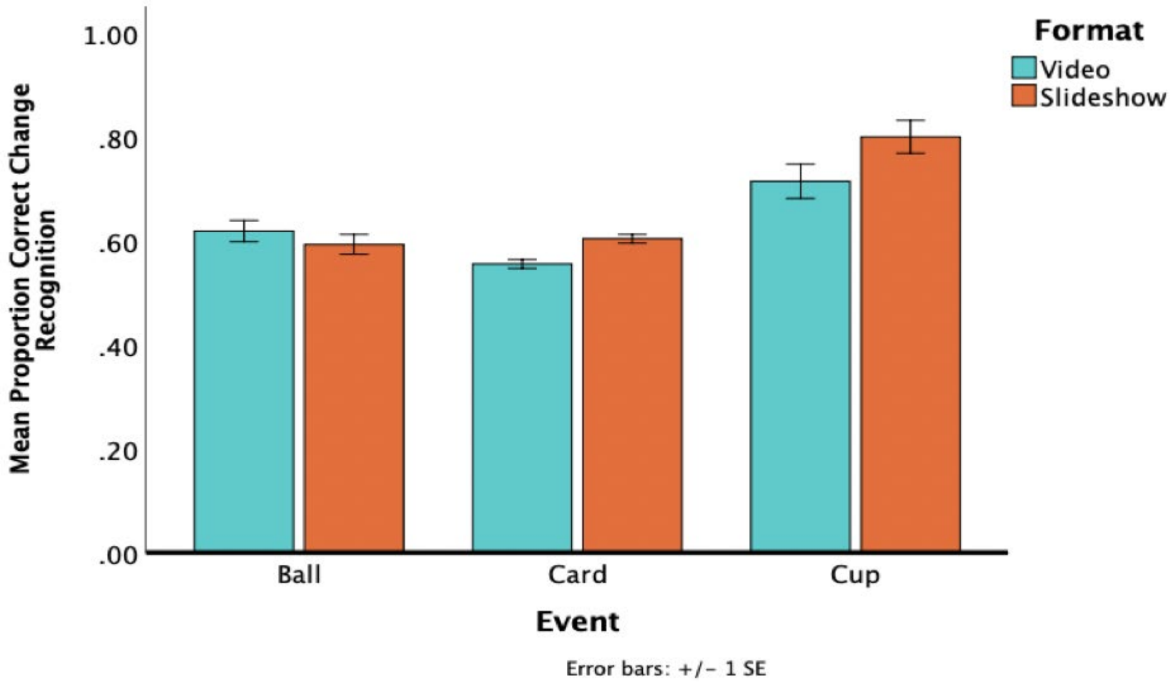

Figure 5: Participants' responses to the change recognition question for the Ball, Card, and Cup events in relation to Video versus Slideshow format

No significant three-way interaction between Condition, Format, and Event emerged in the analysis.

Summary

Taking the change detection results all together, two important findings emerged. First, this study provided clear evidence for replication of change blindness in the videos selected from the internet. This was especially true for the comparison of Easy versus Hard conditions, in that change detection rates were significantly lower in the Hard condition relative to the Easy condition across all three events on all three dependent measures. Put another way, condition differences between Easy and Medium, or Medium and Hard, conditions depended to some degree on the particular event and the particular dependent measure at issue. Overall, however, condition differences in change detection followed the predicted pattern, and tended to be statistically significant.

Second, our findings also provided clear evidence that change blindness occurred when videos were rendered in self-paced slideshow format. In particular, the fact that no significant interaction occurred between Condition and Format variables indicated that condition (task difficulty) affected change detection rates to the same degree in the slideshow format as in the video format.

Count and Confidence Findings

Secondary questions we investigated concerned the extent to which a) error in participants' count estimates for the first series (i.e., the number of ball passes in the Ball event, the number of red cards displayed in the Card event, and whether an actor's hand touched the same cup at beginning and end of the event in the Cup event), and b) their level of confidence concerning those counts, corresponded with whether, and which, instructions they received to count. Analysis of these count errors and confidence responses provided an additional source of information about the validity of the condition manipulation across the Video and Slideshow formats. As well, these analyses were helpful in discovering events for which participants might have had difficulty following task instructions.

Counting Error

We predicted that participants' count estimates would be least error-prone in the Medium condition (in which they were specifically asked to count just that first series), next least error-prone in the Hard condition (in which they were asked to count both the first as well as a second series), and most error-prone in the Easy condition (in which no mention of counting occurred in the instructions). The counting error measure thus served as a check that participants indeed were able to follow instructions across conditions, and the extent to which this might be affected by video versus slideshow format.

We examined participants' error on the first-series count via a 3 (Condition: Easy, Medium, Hard) by 2 (Format: Video vs. Slideshow) by 3 (Event: Ball, Card, Cup) mixed-design ANOVA. The ANOVA revealed significant main effects of Condition, $F(2, 311) = 49.63$, $p = .000$, partial eta squared = .242, and Event, $F(2, 310) = 40.05$, $p = .000$, partial eta squared = .205, as well as just two significant two-way interactions: 1) Condition by Format, $F(2, 311) = 3.60$, $p = .029$, partial eta-squared = .023, and 2) Event by Format, $F(2, 622) = 5.64$, $p = .004$, partial eta squared = .018. Regarding the Condition variable, the pattern of errors followed prediction, with lowest rates of counting error in the Medium condition (Mean = 1.76, SE = .36, CI [1.05, 2.46]), intermediate levels of error in the Hard condition (Mean = 3.50, SE = .63, CI [2.80, 4.20]), and highest levels of error in the Easy condition (Mean = 6.82, SE = .37, CI [6.09, 7.54]). With respect to the Format variable, counting errors were statistically equivalent across the Video (Mean = 3.75, SE = .30, CI [3.16, 4.33]) and the Slideshow (Mean = 4.30, SE = .29, CI [3.73, 4.87]) formats. In relation to events, counting errors were lowest for the Ball event (Mean = 2.19, SE = .19, CI [1.81, 2.57]), intermediate for the Card event (Mean = 3.96, SE = .35, CI [3.26, 4.65]), and highest in the Cup event (Mean = 5.92, SE = .44, CI [5.05, 6.78]). Means for the first-series differed significantly between all events, all p's < .001.

Figure 6 displays the Condition by Format interaction; follow-up analyses to examine the locus of this interaction revealed that count estimates followed the predicted pattern of significant differences (lowest error in the Medium condition, followed by the Hard and then the Easy conditions) in the Video format, whereas in the Slideshow format the pattern of differences diverged from the predicted pattern in one respect: counting estimates did not differ significantly between Medium and Hard conditions (although they trended in the predicted direction). As well, the follow-up analyses revealed that count estimate errors differed significantly by Format in the Easy condition (with lower error rates in the Video than the Slideshow formats), but not in the Medium or Hard conditions.

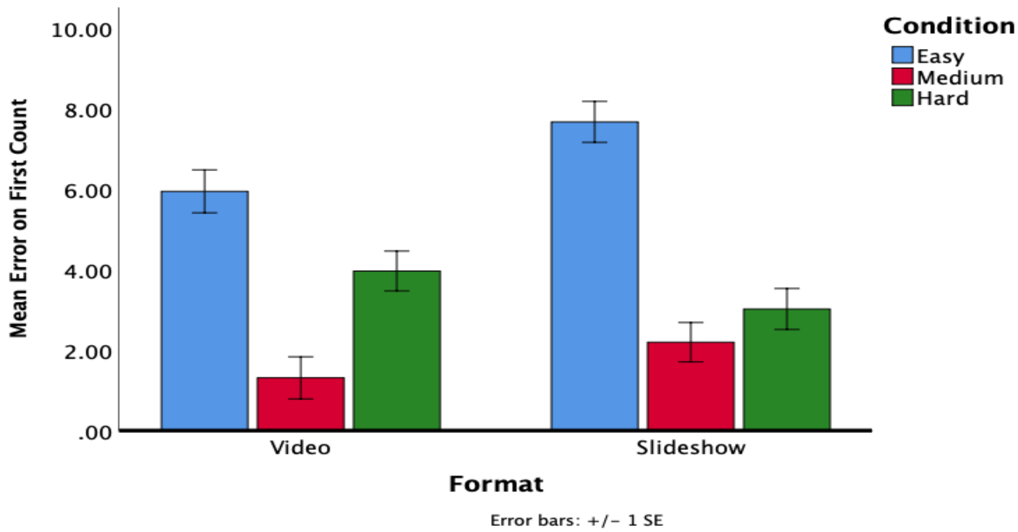

Figure 6: Mean error in participants' estimates on their count of the first event sequence in relation to Video versus Slideshow formats and Easy, Medium, and Hard conditions.

Examining the locus of the Event by Format interaction revealed that count estimates differed significantly between video and slideshow formats only for the Cup event (see Figure 7). In particular, for the Cup event, count events were significantly less error prone in the Video relative to the Slideshow format. As well, follow-up analyses revealed that error rates for the Ball event were significantly lower than for both Card and Cup events in the Video format (but did not differ between Card and Cup events in that format), whereas for the Slideshow format, error rates were significantly lower for both the Ball and Card events than the Cup event, but did not differ between Ball and Card events.

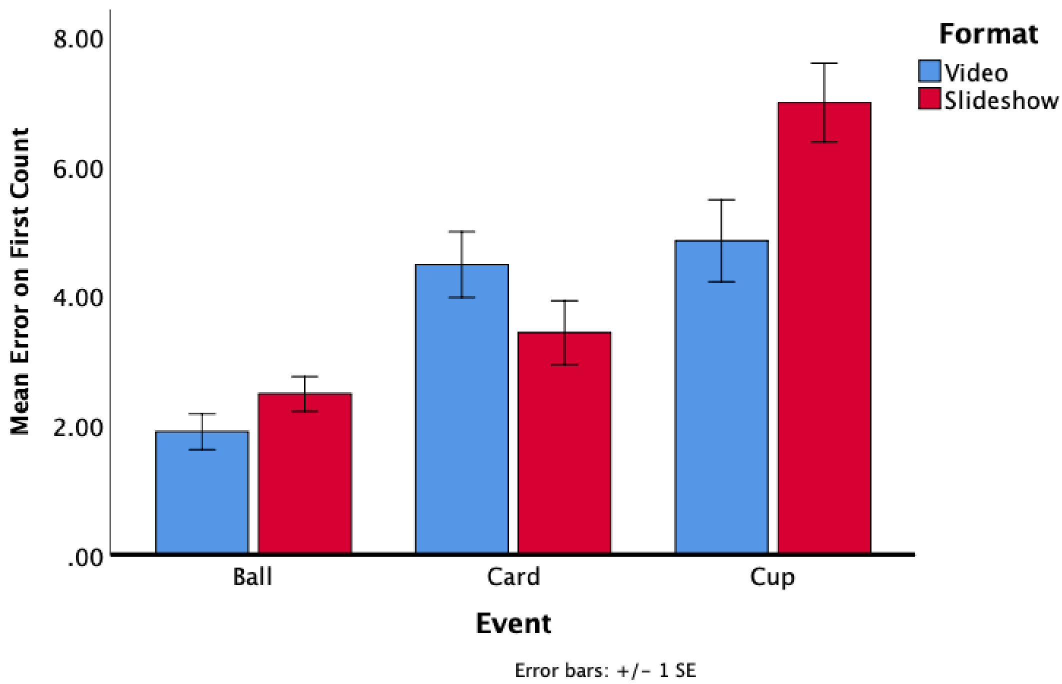

Figure 7: Mean error in participants' estimates on their count of the first series in relation to the Ball, Card, and Cup events in the Video versus Slideshow formats.

In summary, the pattern of findings regarding error in participants' counts of the first series provided general confirmation that they followed instructions while viewing both video and slideshow formats, in that count estimates indeed tended to be significantly lower in the Medium condition than the other two conditions across both formats (with some relatively minor fluctuation in that regard depending on Format and Event).

Count Confidence

We also predicted that participants' level of confidence about their first series count estimates would be highest in the Medium condition, next highest in the Hard condition, and lowest in the Easy condition. Results from a 3 (Condition: Easy, Medium, Hard) by 2 (Format: Video vs. Slideshow) by 3 (Event: Ball, Card, Cup) mixed-design ANOVA confirmed these predictions. The ANOVA revealed significant main effects of Condition, $F(2, 311) = 107.03$, p =

.000, partial eta-squared = .408 (with count confidence patterns of significance in the predicted directions), Format, $F(1, 311) = 4.50$, $p = .035$, partial eta-squared = .014 (with higher count confidence in the Slideshow relative to the Video format), and Event, $F(2, 622) = 85.43$, $p = .000$, partial eta-squared = .216.

Regarding the Condition variable, the pattern of errors followed prediction, with highest rates of confidence in the Medium condition (Mean = 2.72, SE = .06, CI [2.61, 2.83]), intermediate levels of confidence in the Hard condition (Mean = 2.09, SE = .06, CI [1.98, 2.20]), and lowest levels of confidence in the Easy condition (Mean = 1.54, SE = .06, CI [1.42, 1.65]). Means between all three conditions differed significantly from one another, all *p*'s = .000. With respect to the Format variable, confidence ratings were significantly higher for the Slideshow (Mean = 2.19, SE = .05, CI [2.10, 2.23]) than the Video (Mean = 2.05, SE = .05, CI [1.96, 2.14]) format, $p = .035$. In relation to events, confidence was highest for the Ball event (Mean = 2.44, SE = .04, CI [2.36, 2.53]), Intermediate for the Card event (Mean = 2.10, SE = .05, CI [2.03, 2.21]), and lowest for the Cup event (Mean = 1.79, SE = .04, CI [1.71, 1.87]). Confidence means for each of the three events differed significantly from one another, all *p*'s = .000.

As well, two significant two-way interactions emerged in the analysis, Event by Condition, $F(4, 622) = 4.00$, $p = .003$, partial eta-squared = .025 (see Figure 8), and Event by Format $F(2, 310) = 12.96$, $p = .000$, partial eta-squared = .077 (see Figures 8 and 9, respectively). No other interactions were statistically significant. Follow-up analyses revealed that confidence levels differed significantly between the Ball and both Card and Cup events (but not between Card and Cup events) in both Easy and Hard conditions, whereas in the Medium condition, significant differences in count confidence occurred between both Ball and Card relative to Cup events (but not between Ball and Card events). It was noteworthy that count confidence levels were in the predicted direction, and significantly so (highest for the Medium condition, followed by the Hard and then Easy conditions) for all three events.

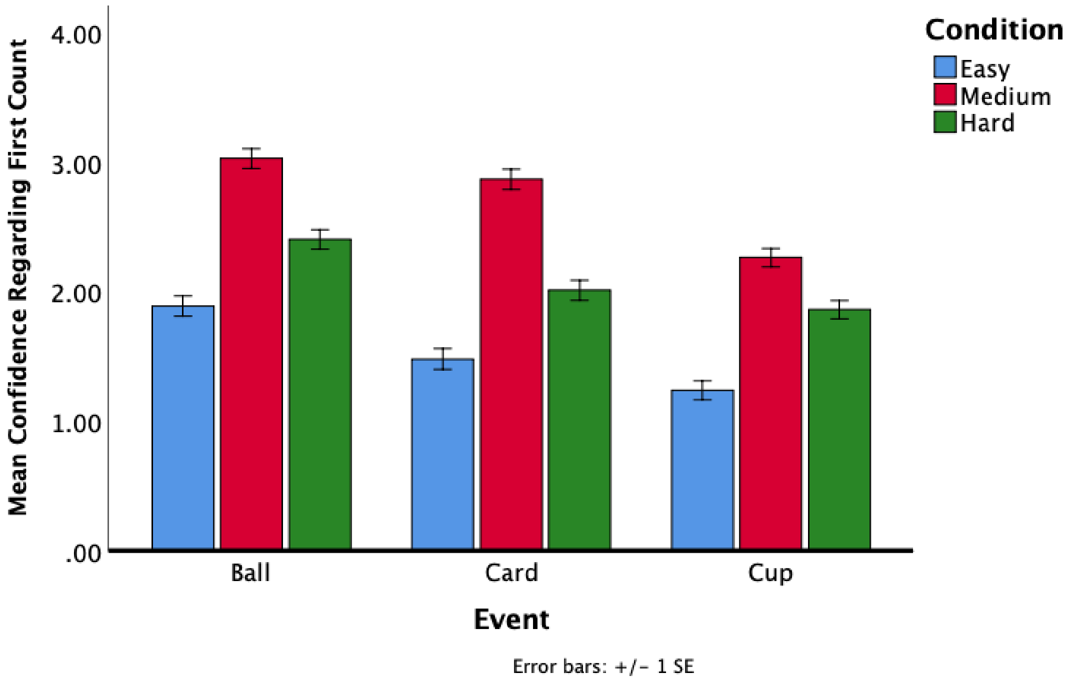

Figure 8: Participants' confidence ratings in relation to their count of the first series for the three events in the Easy, Medium, and Hard conditions.

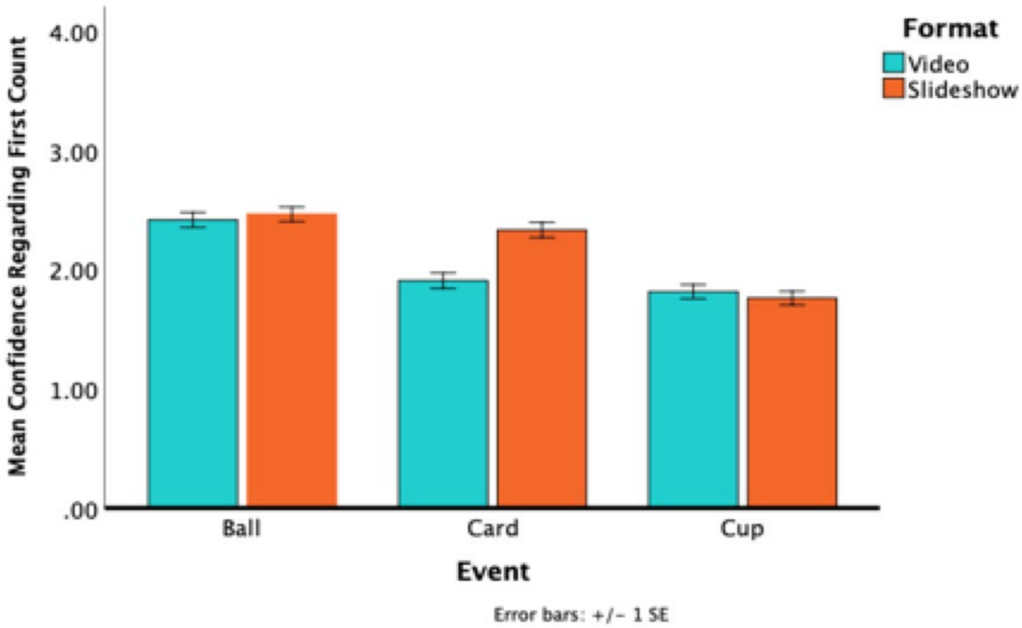

Figure 9: Participants' confidence ratings in relation to their count of the first series for the three events in the Video and Slideshow formats.

In sum, count confidence findings generally mirrored findings regarding error rates in count estimates, and findings on both measures confirmed predictions, by and large. Together, these findings instilled reassurance that participants were adhering to the instructions across conditions in both video and slideshow formats, speaking to the validity of the change detection findings across conditions and formats. At the same time, significant interactions emerged for count errors and count confidence between the three events and both the Condition (Easy, Medium, Hard) and the Format (Video, Slideshow) at issue, indicating that participants had greater difficulty following task instructions with some events than others. The Cup event particularly stood out as challenging in this way, with high levels of count error and low levels of count confidence.

Discussion

The primary goals for study 1 included both replication and novel findings. Regarding replication, study 1 aimed to reproduce change blindness within the videos depicting event sequences that we selected for the study. For novel findings, study 1 attempted to identify change blindness patterns within the same event sequences when transformed into slideshows, an analysis that had not previously been explicitly performed in the literature. We hypothesized that change blindness would occur for the chosen event sequences in both the video and slideshow format. Specifically, we hypothesized that the typical pattern seen in change blindness studies – decreased change detection rates as task difficulty increases – would appear in both video and slideshow formats of the selected event sequences.

Study 1 findings clearly indicated successful replication of change blindness findings within the videos selected from the internet, in that change detection decreased significantly as viewers engaged in increasingly attention-demanding tasks. Moreover, Study 1 findings also provided clear evidence of change blindness when videos were rendered in a self-paced slideshow format, in that increased task difficulty in the slide show format also produced significant decreases in change detection rates. Together, these two findings gave us confidence to proceed, in Study 2, with deploying the dwell-time paradigm to investigate the extent to which attentional patterns occurring during participants' viewing of the events might predict their subsequently reported change detection rates.

At the same time, however, in Study 1 the impact of task difficulty on change detection rates in both video and slideshow formats depended on the particular events participants were viewing, as clarified by significant interactions between the event variable with both the condition and format variables. In the follow-up analyses we undertook to understand these interactions, the cup event stood out as particularly challenging for participants to process. Specifically, for both the count and count confidence measures, participants performed relatively poorly on the Cup event sequence. This likely indicates that participants had the hardest time accurately following instructions for this event sequence, and brought into question if the Cup sequence should be moved into the second phase of research. Ultimately, the poor count and count confidence ratings, combined with a much higher rate of change detection, led to the decision to remove the Cup sequence for study 2.

STUDY 2

Study 2 aimed both to a) replicate previous change-blindness findings from Study 1 with the slideshow format while also b) introducing a new methodology for studying attentional patterns as participants viewed the slideshows. In Study 2, we excluded the cup slideshow due to having observed higher levels of counting error and lower levels of counting confidence for the cup slideshow relative to the other two slideshows.

Regarding attentional patterns, Study 2 used the dwell-time methodology to measure participants' implicit deployment of attention while events unfolded during their viewing of the slideshows. As described earlier, dwell times represent the time viewers spend looking at each individual slide as they advance through slideshows at their own pace, with dwell time operationalized as the latency between clicks of the spacebar as viewing proceeds. As discussed earlier in the introduction, previous research on change blindness has documented close relationships between attention as images are processed and the likelihood of change detection (i.e, the absence of change-blindness), yet such relationships have not previously been examined in the context of streaming events.

In previous dwell-time research investigating event processing, a particular implicit measure of attention during slideshow viewing – higher levels of dwelling to boundary than within-event slides advantage – has been shown to reflect the extent to which viewers are attending to (and will recall) a particular event series within the unfolding activity depicted in the slideshow (e.g., Hard, et al., 2011; Kosie & Baldwin, 2019). This raises the possibility that the magnitude of viewers' dwelling to boundary slides might provide a sensitive measure that predicts viewers' likelihood of subsequently-reported change detection. We specifically predicted that the magnitude of viewers' dwelling to count boundaries (i.e., the boundaries associated with the count series highlighted by task instructions) would be systematically affected by condition (i.e., task instructions to count), and negatively correlated with their subsequent change detection (as measured by proportion correct and questions regarding having noticed unusual or background events). We also predicted that dwell times to unusual background events within the slide show would positively predict participants' subsequently reported change detection performance.

Method

Participants

A total of 385 individuals recruited from the University of Oregon volunteered to participate in the second phase of research. After removing incomplete responses and filtering the data for participants who did not follow the instructions, 243 participants' data were included in Study 2 analyses. Participants earned 1 credit for completing the study. Of the 243 participants whose data were included (M_{age} = 19.6, SD = 1.60), 59.2% were female, 33.6% were male, 2.9% gender fluid, 2.5% transgender, and 4 participants declined to respond. Race/ethnicity for the sample of 243 participants was 65.7% white, 10.7% Asian, 4.3% black or African American, 1.3% American Indian or Alaskan Native, 1.3% Native Hawaiian or Pacific Islander, 10.7% other, with 14 people declining to provide a response. Consistent with the first study, the study's protocol was approved prior to research by the University of Oregon's Office of Research Compliance.

Materials

Stimuli Creation

Study 2 included two of the slideshows used in the first study (the card and ball slideshows). In addition to these two slideshows, a slideshow depicting an individual packing a suitcase (described in Ross & Baldwin, 2015), and a slideshow displaying an individual tying their shoes were also used in this study (described in Kosie & Baldwin, 2019). These two slideshows were included purely for replication purposes, to ensure that the on-line version of the dwell-time paradigm that we utilized for the first time in this research (Garofolo, et al., in preparation) successfully replicated previous in-lab dwell-time findings. Findings to be reported elsewhere confirmed such replication (Baldwin, et al., in preparation), and will not be considered further in what follows.

Slide Classification

For two of the event sequences in Study 2 (Ball and Card), expert coders (two of the study authors) provided judgments classifying slides as depicting specific slide types. These slide type judgments were used to analyze predicted trends in dwell-times. Slide classifications for the Ball and Card event sequences followed methods previously established in the literature and were coded specifically for the change blindness events in the study (boundary vs. within; for boundaries: first-series count boundary, second-series count boundary, non-count boundary; and/or unusual background change). The use of expert slide-type judgements is backed by previous dwell time research (Kosie & Baldwin, 2019). Rather than other methods to establish boundaries, like participant judgements, expert judgements display less variability and prior research confirms the value of expert judgements in the analysis of dwell time patterns (Kosie & Baldwin, 2019).

Procedure

For Experiment 2, participants participated in an online Qualtrics survey that provided informed consent information, introduced the study and all task instructions, as well as asking all questions related to task performance. Self-paced slideshow viewing was performed through a newly developed on-line technique mounted on the research platform Pavlovia (*Pavlovia*, n.d.). Handling both the presentation of the images, and recording dwell-times, this methodology was created by Nicco Garofalo and colleagues in specific preparation for Study 2 (Garofalo, in preparation).

Following a consent page and demographic questions, participants began the study. After task instructions were provided participants were instructed to follow a link embedded in the Qualtrics survey to a slideshow that would appear in a different tab. Subjects would then watch that slideshow one time at their own pace, and then close the slideshow to continue following the survey. For each participant, this process was repeated with each of the slideshows (note that only Ball and Card slideshow data were relevant to the present thesis).

The first link participants were directed to brought them to the suitcase action sequence. This acted as a practice slideshow to aid in familiarizing participants with the process of the study. Following viewing of the practice slideshow, participants returned to the questionnaire and repeated this process for the two event sequences that were analyzed in this thesis. Dwell-time data were collected as participants viewed these slideshows. The Ball and Card slideshows were presented in randomized order.

Participants were randomly assigned to one of three conditions Easy, Medium, and Hard. As in Study one, participants in the Easy condition were instructed to simply watch the two videos, participants in the Medium condition were instructed to watch the videos while keeping track of the number of times a specific event occurred in the video, and participants in the Hard condition were tasked with count two series within the event sequence at the same time.

Participants responded to the same set of questions following viewing of the Ball and Card slideshows that were asked in Study 1. Finally, participants provided responses to an ADHD questionnaire; these responses are not presented in this thesis. Participants were also asked following completion of the study to disclose how closely they had followed instructions.

Design

Study 2 included one between-subjects variables: Condition (Easy, Medium, Hard). As well, it included the repeated measures variable of Event (Ball, Card). Dwell-times during slideshow viewing were collected for both slide shows. Participants in all conditions provided answers to a series of three change-detection questions for each event, as well as answers to questions about their best estimate of the first series count and their level of confidence about their estimated count.

Measures

Change Detection

Change detection was measured by the same questions used for this purpose in Study 1 (proportion correct change recognition, identification of unusual events, and identification of background events).

Count Performance

Following the same method as in Study 1, prior to answering any questions relating to change blindness, participants were first instructed to immediately provide the counts they had been instructed to track. Participants in all three conditions provided their best estimate of the first series count (as well, participants in the Hard condition provided estimates of the second series count; these data were not analyzed) and then responded to a confidence question that asked observers to rate their confidence of the estimate of the first series count on a scale from "Not at all confident" to "Very confident."

Dwell Time Measure

Dwell time was measured by indexing the latency between one space bar click to the next via custom-created Java code mounted on the online data collection service known as Pavlovia. Following typical procedure for dwell-time research, dwell times for the first several slides in each event sequence were removed from analysis (Kosie & Baldwin, 2019). To correct for positive skew present in our data, which is typical for dwell time research, dwell times distributions were normalized via a $\log_{10}$ transformation, with outlier dwell times that were three standard deviations greater from the group mean being removed from analysis.

Results

Behavioral Findings

Given event differences in change detection rates observed in Study 1, in Study 2 we opted to analyze behavioral findings for the Ball and Card events separately. We also opted to streamline the analysis by creating a composite measure of change detection comprising the three dependent measures related to change detection: proportion correct in change recognition, identifying that unusual events occurred, and identifying that background events occurred. Study 1 MANOVA findings clarified that all three measures were sensitive to task difficulty (i.e., differences across Easy, Medium, and Hard conditions), providing a strong rationale for creating a change-detection composite.

Two one-way ANOVAs examining the change-detection composite across the three conditions (Easy, Medium, Hard) separately for the Ball and Card slideshows revealed that change blindness patterns generally replicated Study 1 findings for the Card slideshow, but not the Ball slideshow.

Specifically, for the Ball slideshow (Figure 10), the ANOVA revealed no significant main effect of condition, $F(2,240) = .18$, $p = .838$, whereas a significant main effect of condition did emerge for the Card slideshow (Figure 11), $F(2,240) = 5.51$, $p = .005$, partial eta-squared = .044, with significantly higher levels on the change detection composite for the Easy condition relative to both the Medium ($p = .010$) and Hard ($p = .005$) conditions, but no significant difference between the Medium and Hard ($p = .641$) conditions.

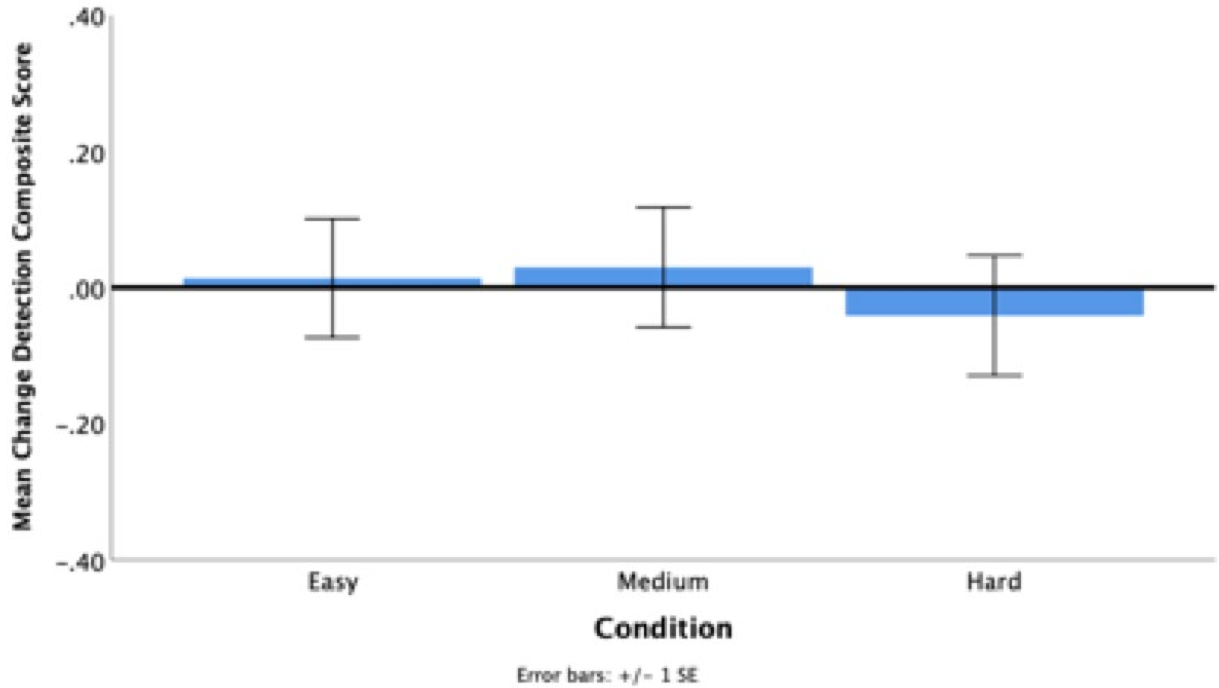

Figure 10: Mean change detection composite scores for the Ball slideshow across Easy, Medium, and Hard conditions.

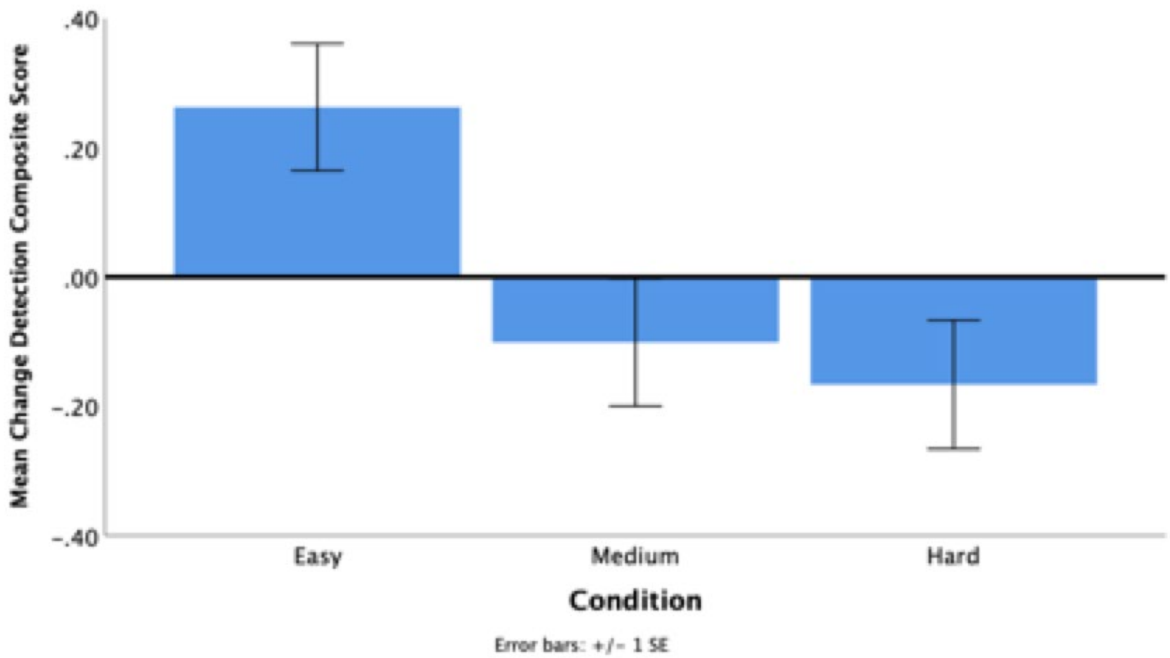

Figure 11: Mean change detection composite scores for the Card slideshow across Easy, Medium, and Hard conditions.

Count Inattention (Count Error and Confidence Ratings Composite)

Given that count error and count confidence ratings both reflect viewers' attention to the counting instruction, we opted to streamline analysis by creating a composite measure. To do so, we reverse-scored viewers' confidence ratings (thus reflecting their lack of confidence), *Z*-scored this measure as well as their count error scores and averaged the two measures together to derive a count-inattention composite score. We undertook separate one-way ANOVAs for the Ball and Card slideshows examining these count inattention composite scores by condition (i.e., Easy, Medium, Hard). This ANOVA with the Ball slideshow revealed a significant main effect of condition, $F(2,240) = 11.10$, $p = .000$, partial eta-squared = .085 (see Figure X). Follow-up analyses revealed that count inattention levels were significantly lower in both Medium and Hard conditions relative to the Easy condition, t's > 2.96, p < .004. Count inattention scores were marginally lower in the Medium condition relative to the Hard condition, $t(159) = 1.95$, $p = .052$.

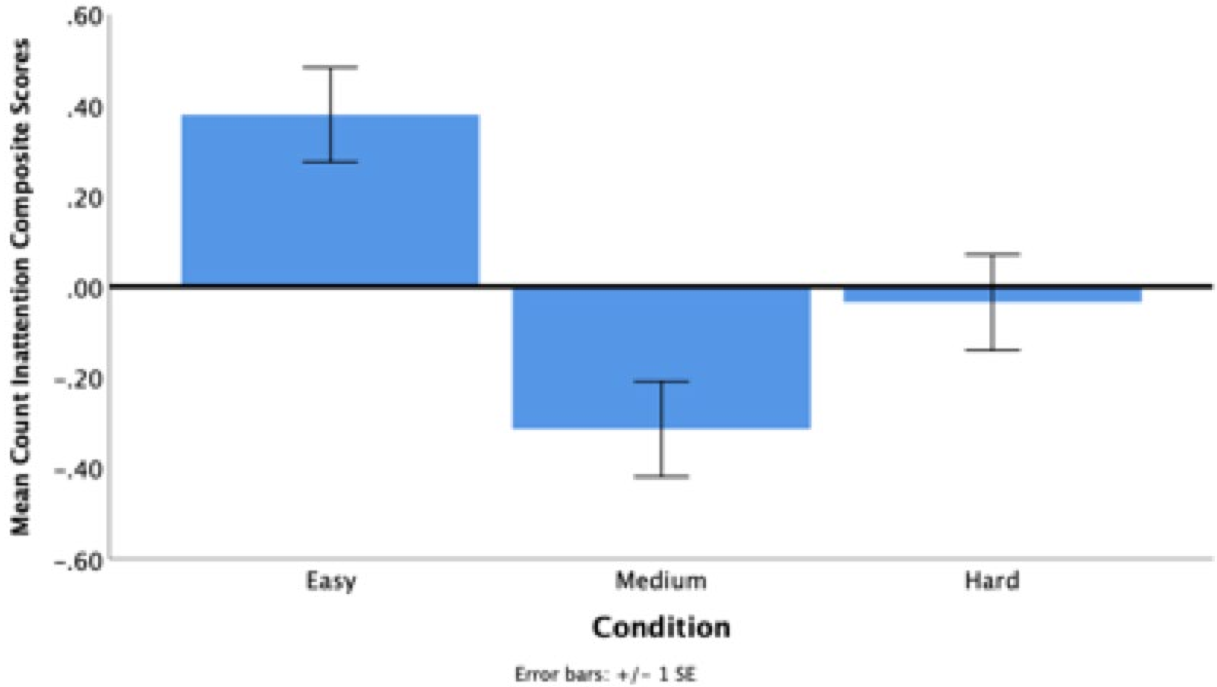

Figure 12: Mean first-series count inattention scores for the Ball slideshow in the Easy, Medium, and Hard conditions.

Similarly, the ANOVA examining count inattention composite scores for the Card slideshow revealed a significant main effect of condition, $F(2,240) = 20.00$, $p = .000$, partial eta-squared = .143 (see Figure X). Follow-up analyses revealed significantly lower count inattention scores for Medium and Hard conditions relative to the Easy condition, t's > 5.49, p's < .000, but no significant difference between Medium and Hard conditions ($p = .321$)

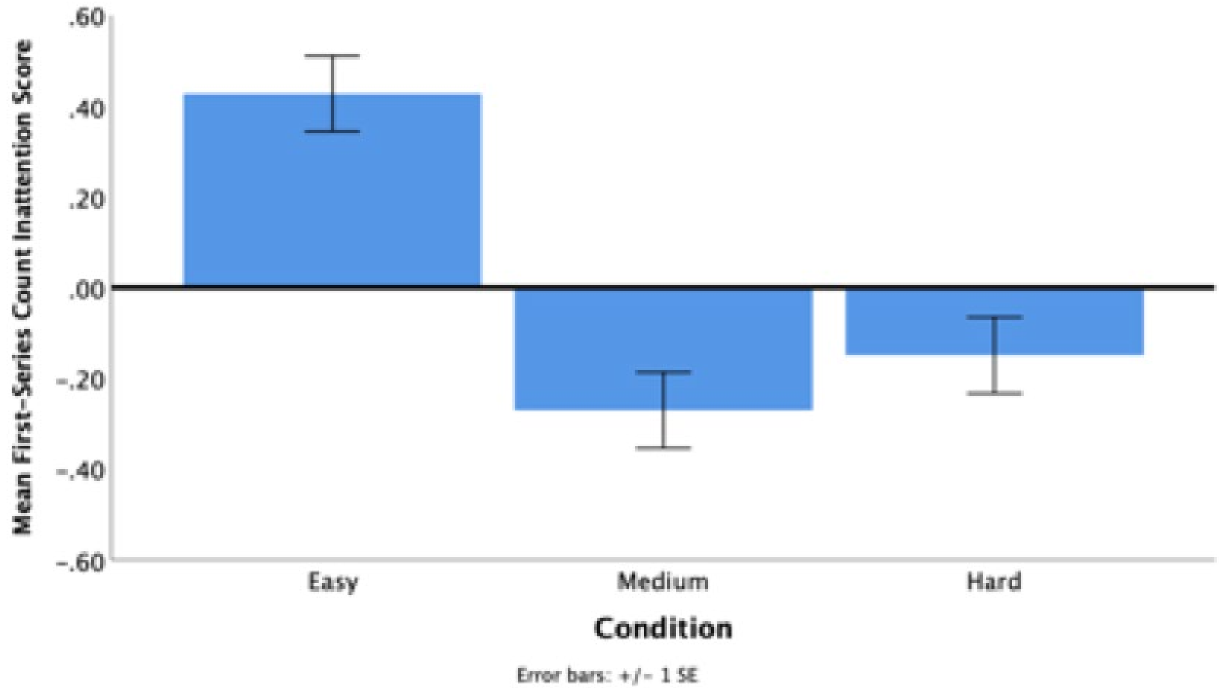

Figure 13: Mean first-series count inattention scores for the Card slide-show in the Easy, Medium, and Hard conditions.

Summary

Study 2 change detection and count inattention scores provided clear confirmation of change blindness with the Card slideshow, in that change detection rates decreased with more difficult task instructions, and predicted condition differences also occurred with count inattention (a composite measure combining count errors and count confidence). These Card slideshow findings set a solid foundation for examining possible relationships between change blindness and participants' dwell-time patterns measured during their actual viewing of the unfolding card slideshow. In contrast, the absence of change blindness patterns with the change detection measure for the Ball event raised questions as to whether such relationships to dwell-time patterns should be expected to emerge with that event. For this reason, in what follows, I present analysis of such relationships with respect to the Card slideshow alone.

Dwell-Time Findings

Replication of Previous Dwell-Time Patterns

As described in the introduction, previous research employing the dwell-time paradigm has reported significantly longer dwelling to boundary slides – regions within unfolding events where one segment ends and the next begins – relative to within-segment slides. Participants' dwell time patterns for the card slideshow replicated this finding: Mean log dwell times within the card slideshow were significantly longer for boundary (M = 2.56, SD = .20) than within slides (M = 2.52, SD = ,18), paired $t(220) = 9.92$, $p = .000$, [.023, .043]. This finding provides important reassurance on two points: 1) previously observed dwell-time patterns are robust across studies and across novel event streams that haven't previously been examined, and 2) the online dwell-time paradigm that we employed for the first time in this thesis derives dwell-time findings with patterns expected based on previous dwell-time research.

Card slideshow slide-type dwell-time differences

Of interest was the extent to which task instructions, which differed across conditions, produced systematic changes in participants' dwell-time patterns. We specifically predicted that dwell times to boundary slides associated with first-series counting would increase in Medium and Hard conditions (in which participants were asked to count the number of red, or red and black cards, respectively) relative to the Easy condition (in which participants were simply asked to watch the slideshow), whereas dwell times to the second-series count boundaries would increase in the Hard condition relative to the Medium and Easy conditions. A mixed-design 3 (condition: Easy, Medium, Hard) X 4 (slide type: First-series boundary, Second-series count boundary, Non-count boundary, Within) ANOVA revealed significant main effects of condition, $F(2,218) = 10.72$, $p = .000$, partial eta-squared = .090, and slide type, $F(3,654) = 173.37$, $p =$

.000, partial eta-squared = 443, as well as a significant condition X slide type interaction, $F(6,654) = 42.95$, $p = .000$, partial eta-squared = .283 (see Figure X).

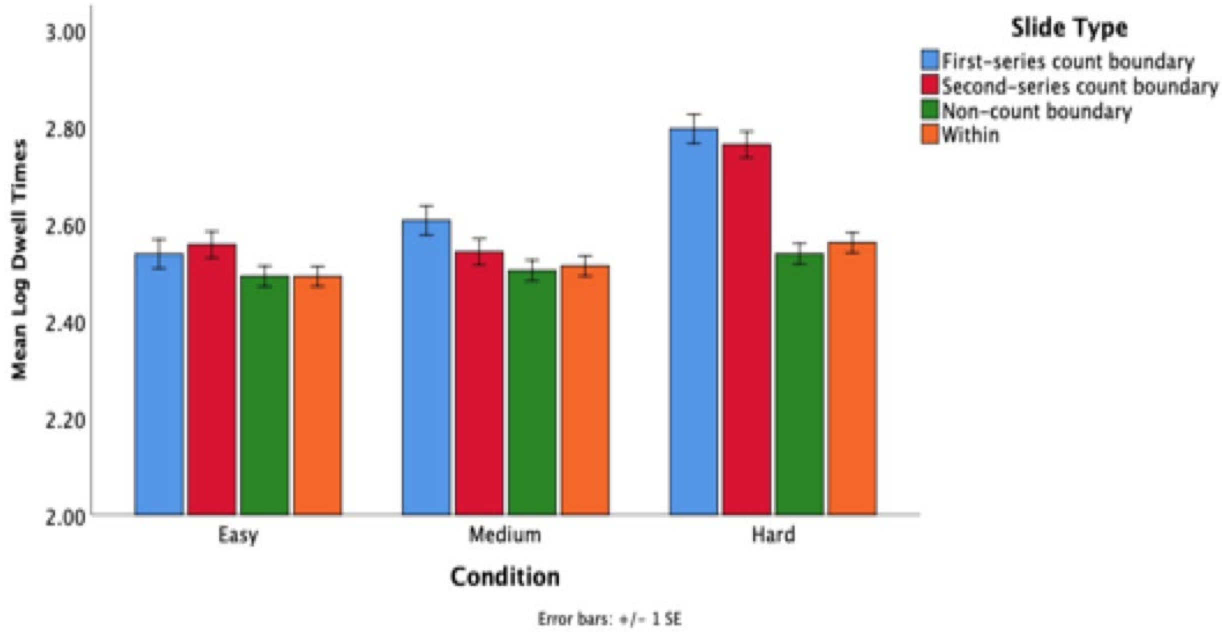

Figure 14: Card slide-show mean log dwell times for the four slide types in the Easy, Medium, and Hard conditions.

Follow-up analyses exploring planned comparisons contributing to the locus of the interaction revealed that, as predicted, dwell times to first-series count boundaries increased significantly in the Medium and Hard conditions relative to the Easy condition, t's > 1.78, one-tailed p's < .039. Also as predicted, dwell times to second-series count boundaries increased significantly in the Hard condition relative to the Medium and Easy conditions, t's > 5.11, one-tailed p's < .000. These findings clearly document the predictable impact of task instructions on viewers' dwell-time patterns.

Also of interest was the extent to which task instructions affected dwelling to unusual background slides. We predicted that dwell times to unusual background slides would be reduced as task difficulty increased (in Medium and Hard conditions relative to the Easy condition), given that reported detection of those unusual background slides reduced with task difficulty. In contrast to our prediction, however, dwelling to unusual background slides was significantly increased in the Hard condition relative to both Medium and Easy conditions (the latter of which did not significantly differ), t's > 2.67, p's < .008. This unexpected pattern may have emerged because dwell times across all slide types tended to be higher in the Hard condition relative to the Medium and Easy conditions, t's > 1.95, p's < .054. That is, increased task difficulty of the Hard condition seemed to have led viewers to slow their self-paced viewing rate overall relative to the two other conditions.

Relationships Between Dwell-Time and Change-Detection Patterns

One of our central questions of interest was the extent to which viewers' attentional patterns, as indexed by dwell times, might predict how likely they were to subsequently report having detected the unusual background changes that occurred within the unfolding event stream. We predicted that enhanced dwelling to count boundaries would be significantly negatively associated with viewers' change-detection scores, whereas enhanced dwelling to both a) other, "off-task" slides, meaning non-count boundary and within slides, and/or b) unusual background slides, would be positively associated with viewers' likelihood of scoring high on change-detection. Of course, we also expected that the task instructions and viewers' apparent success at complying with those instructions (count-inattention composite scores) would predict viewers' change-detection success. We used multiple regression to simultaneously test all these possible predictors of viewers' change-detection scores. Specifically, our regression model simultaneously tested the impact of five predictor variables – condition, count inattention composite scores, count-boundary log dwell times, "off-task" log dwell times, and unusual slide log dwell times – on viewers' change-detection composite scores. This was a significant model, $F(5,215) = 6.32$, $p = .00$, Adjusted R-square = .108. As revealed in Table 1, standardized beta coefficients for all predictors were either significantly or marginally significantly associated with change detection composite score, with individual relationships in the predicted directions, with the exception of dwell times to off-task slides, for which longer dwell times were unexpectedly associated with reduced rates of change detection.

Table 1: Results of the multiple regression analysis testing relationships between five predictor variables and viewers' change-detection composition scores.

Predictor	Beta coefficient	*t*-value	*p*-value
Condition	-.159	-2.098	.037
Count inattention	.132	1.934	.054
Count-Boundary Slide Log Dwell Time	-.818	-2.723	.007
Off-Task Slide Log Dwell Time	-.989	-1.764	.079
Unusual Background Slide Log Dwell Time	1.879	2.388	.018

Taken together, the multiple regression findings indicated that, collectively, these five variables accounted for a significant amount of variance in viewers' change detection. Moreover, even while controlling for the other predictors' contributions, each individual predictor bore significant (or nearly significant) relation to change detection. Of greatest interest here, both viewers' count-related boundary dwelling and their dwelling to unusual background slides were each significantly and uniquely associated with change detection scores, providing clear evidence that attentional patterns during slide-show viewing offer a predictive window into whether viewers will be subject to change blindness.

Discussion

To recap briefly, in Study 2, participants displayed change blindness with the Card slideshow, but not with the Ball slideshow. For this reason, we undertook dwell-time analyses only with the Card slideshow data. Dwell-time patterns displayed the expected boundary advantage that has been repeatedly observed in previous dwell-time research, providing validation for the new on-line dwell-time paradigm and further evidence of this important attentional signature with a new event stream. As well, dwell times to specific slide types, such as first-series count boundary slides, displayed predicted differences in relation to the difficulty of the task instructions viewers were given across conditions. Most strikingly, in a multiple regression analysis, dwell-time patterns to count-boundary slides and unusual background slides were both significantly associated with change detection scores, even while controlling for each other as well as several other key variables (condition, count inattention, and off-task slide dwelling).

On the one hand, these findings provide a striking demonstration of how predictable change detection is in relation to the task viewers are given as they experience the event about which they are tasked. For example, when asked to count specific occurrences within the same event, viewers reorganized their attention to enhance dwelling to boundaries relevant to the count they were instructed to tally. The more they achieved such task-related attentional reorganization, they less likely they were to detect unusual changes in the background.

On the other hand, these findings also provided an altogether new demonstration that dwell-time patterns offer predictive information about the likelihood that viewers will be subject to change blindness. Viewers who displayed high levels of attention to count boundaries were likely to display change blindness. This was so even while controlling for a) other measures of their attention to the counting task, such as the count inattention measure, and b) whether they were given instructions to count. Independent of this effect, viewers who displayed high levels of attention to the unusual background slides were unlikely to display change blindness.

All in all, Study 2 findings provided new evidence of precisely how task instructions shape attentional patterns as people are experiencing unfolding events, and how these attentional patterns, in turn, presage what people sense and encode about those events.

General Discussion

This thesis presents two studies. The aim of the first study was to replicate change blindness in three new event videos and to determine whether the self-paced slideshow format of these same events might be appropriate for investigating change blindness phenomena. Results from Study 1 succeeded at both of these aims. Our findings clearly indicated successful replication of the change blindness effects with the selected event sequences in both a self-paced slideshow format as well as in video format. These findings were particularly exciting as change blindness studies have never before been demonstrated with self-paced slideshows.

In the second study, I measured participants' dwell times while they advanced at their own pace through just two of the Study 1 slideshows (the Ball and Card slideshows). Of central interest in the second study was the extent to which attentional patterns during slideshow viewing, as indexed by dwell times, might offer systematic information about the likelihood that participants would subsequently reveal change blindness. I was able to test this possibility only with the Card slideshow, as the Ball slideshow unexpectedly failed to elicit change blindness in Study 2, despite it having done so in Study 1. With the Card slideshow, I found clear evidence that dwell time patterns provide advance information about change blindness. In particular, participants' dwell times to count-boundary slides as well as to unusual background slides both uniquely predicted the likelihood that they would successfully detect those background changes, even while controlling for task difficulty (i.e., condition), count-inattention scores, and dwell times to off-task slides. This is the first evidence to date that attention to specific junctures within unfolding events – such as task-related boundary slides and unusual background change slides -- enable prediction of change blindness. More specifically, my findings link specific aspects of attentional reorganization due to task instructions, such as enhanced attention to specific event boundaries, with subsequent change blindness. These findings illuminate the change blindness phenomenon in new ways, and suggest new real-world applications for the dwell-time methodology.

Limitations and Remaining Questions

The data presented in this study was collected using a large dataset that involved multiple independent studies. The large number of participants, combined with the fact that we replicated our own findings within this study speaks to the robustness of the findings. That said, there certainly were some limitations. Regarding the generalizability of findings, change blindness and dwell-time findings have not been shown to be influenced by gender, but it is important to note that all studies contained considerably more female participants than male. In addition, as these data were collected from students at the University of Oregon, this study draws conclusions from a largely Western, Educated, Industrialized, Rich, and Democratic group of participants. Research has shown that findings from WEIRD participants are not representative of cognitive functioning cross-culturally, with WEIRD participants being described as “frequent outliers” in comparison to the rest of the world (Henrich et al., 2010).

A further concern is that some of the events utilized in this study failed to replicate when tested. With the Ball event sequence failing to replicate change blindness findings, this important limitation demonstrates the need for replication in all studies. The reason for this replication failure is unknown, but one possibility is that change detection rates tended to be lower for the Ball slideshow than either of the other two slideshows (Card and Cup) in Study 1, and relative to the one other slideshow (Card) in Study 2. Perhaps a “floor effect” was operating with the Ball slideshow that interfered with detection of difficulty-related differences in change detection. It will be important, in future research, to collect additional data with more event sequences, and event sequences that avoid such a floor effect, to understand the robustness of the present findings.

Broader Implications

The findings reported in this thesis hold significant real-world implications. For one, the findings of this study will help guide future research. The online format of dwell time research used in this study is particularly significant. In the past, all dwell time research has been conducted in a lab setting. This dwell time research project has been fully adapted to be performed in an online setting. Replication of previous dwell time findings in the online format marks a significant advance in the accessibility and feasibility of future dwell time studies. In addition, the replication of change blindness in a slideshow format is also of significance as it allows new types of change blindness studies to be undertaken than what has previously been performed.

Further, the present findings extend what has been known about dwell-time indices of attentional patterns during event processing and their cognitive implications. Furthermore, these findings may help contribute one day to a variety of different real-world problems. Specifically, it may one day be possible to utilize dwell-time patterns across a range of situations where monitoring the focus and adequacy of people's attention is crucial. For example, applications could include a) refinements to diagnosis in those with attentional impairments, such as attention-deficit hyperactivity disorder, dementia, and severe brain injury, and b) the creation of systems that alert people when their attentional patterns have become suboptimal for an essential task, such as drivers, train operators, pilots, and air traffic controllers.

Future Directions

With the findings from this study, many new possibilities for future research can now be explored. The development of an on-line system that collects dwell-time information makes creating and launching dwell-time studies much easier. As the dwell-time patterns typically seen in the literature were present in this study, it is now potentially possible to perform many more large-scale dwell-time studies than ever before. Future directions for dwell-time research should be aimed at expanding the current literature with large-scale, and potentially even cross-cultural, studies that examine even more complex event sequences. This will allow for both findings about the true generalizability of dwell-time research, and also help to continue identifying the exact depth of information that dwell-time provides.

The present findings also showcase ways in which an understanding of change blindness can be expanded by using the dwell-time methodology. Future research should aim to evaluate a larger set of more diverse stimuli. Future research should also aim to use a mix of event sequences found online, as well as sequences created for specific studies that aim to identify exactly when and what types of unexpected changes people are most likely to miss. One possibility to test this question would be to create multiple identical event sequences, which contain change blindness phenomena, but to different degrees. For example, one sequence could have the change be very central, whereas another sequence could have the change more in the periphery. This would allow for interesting findings about the types of changes that most often go unnoticed and may ultimately help to improve cognitive functioning in real-world scenarios where change blindness occurs.

Conclusion

Taken altogether, my findings demonstrate the power that dwell-time has as a tool for data collection. I found that dwell-times provide predictive information about the probability that a viewer will be subject to change blindness. This finding both opens the door to future studies of change blindness and dwell-time, and also grants new insights into the precise attentional mechanisms that create the change blindness phenomenon.

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