INDIVIDUAL DIFFERENCES IN ATTENTION CONTROL AND CHANGE BLINDNESS

by

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A Dissertation
Submitted to the
Graduate Faculty
of
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of
Doctor of Philosophy
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Master of Arts
George Mason University, 2012

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DEDICATION

This is dedicated to my parents Jorge and Maria, who without their continued support and encouragement this work would not be possible.

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I would like to thank the many friends, relatives, and supporters who have helped make this work possible. Specifically, my brother who helped debug early versions of my change blindness tasks, Molly Martini who piloted my experiments, Ivonne Figueroa and Pamela McGee who edited early versions of my dissertation proposal.

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LIST OF ABBREVIATIONS

Cognitive Flexibility	CF
Working Memory Capacity	WM
Visual Short Term Memory	VSTM
Bayesian Data Analysis	BDA
Hamiltonian Monte Carlo	HMC
No-U-Turn Sampler	NUTS
Markov Chain Monte Carlo	MCMC
Region of Practical Equivalence	ROPE
Widely Applicable Criterion	WAIC
Youmans Cognitive Flexibility Assessment	YCFA
Operation Span	Ospan
Reading Span	Rspan

ABSTRACT

INDIVIDUAL DIFFERENCES IN ATTENTION CONTROL AND CHANGE BLINDNESS

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Change blindness is a well-studied perceptual phenomenon that demonstrates the volatility of the human visual system. Although its effects are ubiquitous, they do not manifest themselves in the same way in all observers. This dissertation explores the relationship between individual differences in attentional control, specifically differences in cognitive flexibility and working memory capacity, and change blindness in the presence of relevant task knowledge and task load. Results indicate that both cognitive flexibility and working memory predict change blindness independently, but can also interact in the presence of relevant task knowledge.

CHAPTER ONE

Although most individuals firmly believe their conscious experience of the world is accurate, complete, and reliable, considerable evidence lies in opposition to this notion. The phenomenon of *change blindness,* the tendency for observers to miss large changes in visual scenes during brief perceptual disruptions, has garnered interest from many areas of cognitive science by highlighting the weaknesses of our visual memory systems and the volatility of our internal representation of the world (O'Regan, 1992; Rensink, O'Regan & Clark, 1997). The phenomenon has been shown to persist when changes in visual scenes are briefly masked (Rensink et al., 1997), paired with salient 'mud splashes' (O'Regan, Rensink & Clark, 1999), during eye movements (Grimes, 1996) and when objects obscure perception in the real world (Simons & Levin, 1998).

Change blindness is relevant to a variety of human factors applications because human operators are often responsible for visually monitoring systems, instruments or other external information sources in order to maintain safe and efficient performance. Furthermore, most real-world environments require constant attentional shifts, distractions and interruptions. However, if operators fail to detect state or environmental changes, unsafe or suboptimal behaviors become more likely to occur (Youmans & Ohlsson, 2008). Understanding and describing the environmental and operator characteristics that underlie change blindness is critical for developing systems that adapt or correct for lapses in visual attention. Specifically, in this dissertation I explore 1) how individual differences in attention control interact to predict change blindness and 2) how these individual differences are influenced by task relevant information and difficulty.

What Causes Change Blindness?

The physiological reasons for the phenomenon of change blindness are well documented (Grimes, 1996). Under normal conditions, without visual occlusions, the human attentional system automatically orients to abrupt variations in local luminance, allowing changes in the visual field to be easily detected (Grimes, 1996). However, because change blindness paradigms always include some type of occlusion or concurrent visual onset (which swamp the local luminance changes produced by the change object), observers are unable to leverage automatic attentional capture and must instead engage in some form of slow and deliberate visual search.

Although the physiological causes for change blindness are generally agreed upon, the cognitive mechanisms responsible for the phenomenon are not well understood. Some researchers have argued that humans offload the majority of information about the visual world onto the environment itself, using it as a kind of external memory (O'Regan, Rensink & Clark 1999). This implies that change blindness occurs because observers lack any internal representations of the world and are simply falling prey to a strong belief in stability of the environment. Under this hypothesis, changes can only be detected if attention is focused on the changing object and the representation is maintained in short-term memory. However, Simons, Chabris and Schnur (2002) have argued that change blindness can occur even when internal representations are maintained. This suggests that change blindness occurs because observers fail to compare preserved representations, rather than because representations are not present at all. In a real world change blindness task, Simons et al. (2002) found typical rates of change blindness whereby approximately 50% of observers in the study failed to notice that an object held by a confederate either appeared or disappeared. However, when probed, the majority of observers revealed they had encoded the presence or absence of the object, but failed to notice the change when it occurred. In order to understand how observers might fail to notice changes to objects that have been viewed and internally represented, it is worthwhile to consider *how* observers extract information from the environment through visual search.

Scene features

Henderson (2003) has shown that visual search in natural scenes is predominantly guided by top-down processes rather than bottom-up factors, i.e. salience. Observers tend to fixate on objects that are germane to the context of the scene, leveraging short-term information about previously attended objects, as well as long-term representations of scene schemas. The top-down nature of visual search is evident in differential change blindness rates for contextually different change objects. For example, Rensink et al. (1997) demonstrated that observers identified change objects that were of central interest to the scene more quickly and accurately than if the change object was of marginal interest. Furthermore, research from Beck, Angelone and Levin (2004) and Beck, Levin and Angelone (2007) has shown that the typicality and probability of change objects can impact change blindness rates. Researchers found that improbable or atypical changes (e.g. windows appearing/disappearing) were less likely to be detected than probable and/or typical changes (e.g. blinds opening and closing). Thus, violations of scene schemas and expectations represent *scene features* of change blindness tasks, which mediate the difficulty of detecting changes within a scene. In addition to scene features, observers themselves may possess characteristics that make them more less likely to detect changes, which I will describe here as *observer features.*

Observer features

Although change blindness is a ubiquitous effect, all observers do not experience the phenomenon equally. Researchers typically find considerable variation in change detection rates, indicating that some observers find changes quickly while others search unsuccessfully. Currently, there are few studies that have explicitly examined the impact of individual differences on change blindness. In general, the literature suggests that attention and memory play a considerable role. Notably, Pringle, Irwin, Kramer & Atchley (2001) found that individuals with larger attentional breadth as measured by the Useful Field of View task (UFOV; Ball & Owlsey, 1991) found changes more quickly in a real-world driving scenes. More recently, Jensen (2011) replicated these findings, but failed to find reliable correlations between personality measures and incidental change detection, intentional change detection, or an inattentional blindness task. In addition, Asano, Kanaya and Yokosawa (2008) found that proofreaders found more changes than novices in a change detection task with real world scenes. The authors conclude that proofreader may have “a highly developed ability for spatial attentional allocation that is generally applicable to attentional demanding search situations where both detection targets and distractors are not predesignated.” Furthermore, Rensink (2008) states that in addition to individual differences in how observers prioritize information in visual scenes (e.g. differences in what may be of central interest in a real-world scene) and cultural differences in encoding (Angelone & Severino, 2008; Masuda & Nisbett, 2006), differences in observers' ability to control their attention may predict the ability to detect changes.

In conclusion, the current literature suggests that there may be some reliable observer characteristics related to attention control that yield better noticing behavior, however it remains unclear what cognitive mechanisms may be underlying these relationships. In addition, the studies reviewed above only examined observer characteristics for change blindness tasks using real-world scenes – leaving open the question whether the relationship between observer features and noticing behavior is be contingent on the semantic content of visual information. Thus, it is currently unclear whether observer characteristics can reliably predict change blindness without leveraging schemas and top-down knowledge structures. Furthermore, it is unclear what specific cognitive individual differences in attention control may predict the incidence of change blindness

Role of Working Memory

Because of the established role of focused attention (Rensink et al., 1997; Rensink, 2000) and role of attention control (Asano, et al., 2008), in change blindness tasks it seems natural to assume that individual differences in working memory capacity (WM) should predict change detection speed and accuracy. Kane and Engle (2000) and

Kane, Bleckley, Conway and Engle (2001) have shown that WM is reflective of an individual's ability to control their attention, particularly in regards to overcoming proactive interference. High WM individuals maintain better focus and become less distracted by irrelevant stimuli (de Fockert et al., 2001) and subsequently perform better in a host of other cognitive tasks and social outcomes (Conway, Kane & Engle, 2003). Based on the close relationship between WM and focused attention, the nearly ubiquitous positive aspects of higher WM, and the important role of attention in change blindness tasks, one would expect a positive predictive relationship between WM and change detection. However, available experimental evidence runs somewhat counter to these notions. For example, Smilek, Enns, Eastwood and Merikle (2006) demonstrated that instructing participants to "relax" their attention when searching for a target in a visual search task yielded greater search efficiency over a more active search strategy, when set size was large. They then replicated these findings without instructions by introducing a concurrent memory task designed to tax working memory and prevent a focused visual search. Based on Smilek et al.'s (2006) results one can infer that perhaps, paradoxically, individuals with lower WM, i.e. individuals with fewer available processing resources analogous to participants in the dual task condition of Smilek et al.'s (2006) study, might perform better on change blindness tasks. Watson, Brennan, Kingstone and Enns (2010) replicated Smilek et al.'s (2006) findings while participants had their eyes tracked. Once again, Watson found that the passive cognitive strategy, whereby participants experienced the target 'popping' into view, yielded greater search efficiency. In addition, passive searchers, made fewer saccades and had longer fixations, thereby demonstrating a connection between cognitive strategy during search and occulomotor activity. Finally, Colflesh and Wiley (2013) explored the effects of alcohol on WM and change blindness. Their results showed that intoxication produced a decrease in WM, but an increase in change detection speed. They concluded that alcohol myopia was consistent with a diffusion of attention rather than narrowing of the attentional field, implying that diffuse attention yields higher change detection.

In all three cases described above, the researchers used the term 'diffuse attention' or a 'passive' cognitive state. However, it is important to illustrate that these finding on the surface stand in direct contrast to Rensink's (2000) findings which suggest that *focused* attention is required to find changes. Thus, rather than simply a truly diffuse attentional state, what researchers are instead observing are differences in rates of rates of attentional capture.

Working Memory Capacity

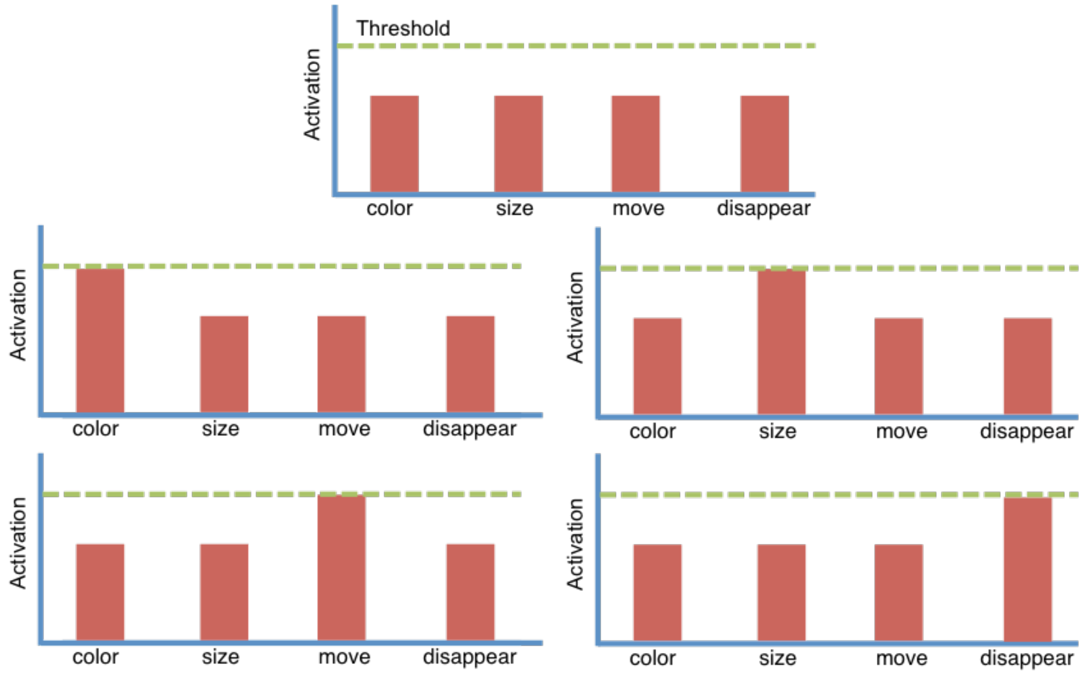
Conway, Cowan and Bunting (2001) explored the relationship between WM and attentional capture and found that individuals lower in WM were actually better at detecting their names in the unattended stream during a dichotic listening task than their high WM counterparts. Conway et al. (2001) took this as further evidence that WM represents attention control and is robust to distractors that normally produce automatic orientation. However, these findings could also be interpreted as suggesting that lower WM may indeed be beneficial to change detection. In contrast to this notion Colflesh and Conway (2007) revisited the findings of Conway et al. (2001), but told participants that they might hear their name in the, otherwise irrelevant, stream. In this study, the effect observed by Conway et al. (2001) was reversed. Individuals low in WM were unable to divide their attention effectively, and performed worse than their high WM counterparts. Furthermore, high WM individuals performed better when they were not required to shadow the relevant stream. Based on their findings Colflesh and Conway (2007) suggest that perhaps WM is also related to the ability to dynamically shift attention based on changes in task demands.

These findings appear to stand in contrast to Colfelsh and Wiley (2013), whereby decreases in WM after drinking alcohol resulted in improved performance on a change blindness task. In addition, the improvement in performance for high WM individuals when not asked to shadow the irrelevant stream observed by Conway & Colflesh (2007) differs from Smilek et al. (2006) and Watson et al.'s (2010) findings. Aside from differences in modality and experimental manipulation, perhaps the clearest methodological difference between these studies and Colflesh and Conway (2007) is that, in the change blindness task, observers were not aware of what the changing object or search target would be; compared to dichotic listening task where the target was the participant's name and participants were told to listen for it. Thus Colflesh and Conway's (2007) conclusions about the nature of WM may be omitting a critical aspect of contextual knowledge. WM may aid in dynamic attention shifts *only when observers are aware of the task at hand*. High WM individuals may, in contrast, be at a disadvantage when attempting to divide attention in an ill-defined context. Smilek et al. (2006) and Watson et al.'s (2010) results also support this notion, because observers did not, naturally, know target locations prior to visual search. Thus it remains open whether other aspects of attention may be involved in attentional capture in ill-defined contexts. For this I turn to a discussion of the literature related to attentional capture more broadly.

Attentional Capture

Folk, Remington and Johnson (1992) put forth that, contrary to the dominant view of the time, attentional capture is: 1) not relegated to motion onsets and 2) something that can be tuned by executive processes. Folk, Remington and Wright (1994) found that motion, size and color all produce attentional capture, but only in feature-specific contexts. For example, 100% false color cues only captured attention when observers were searching for a color onset target. 100% false motion and size cues did not produce these effects and vice versa. Thus, in Colflesh and Wiley (2013), for example, perhaps the ‘diffuse’ attentional state is a form of detuning the attentional system to be less specific, but more in line with the ill-defined context of the task. Alternatively, the diffuse attentional state may be indicative of sporadic shifting or rapid oscillation between attentional tuning states. For example, Folk et al. (1994) describe a “salience threshold” which is what subjects selectively tune depending on task parameters. Diffuse attention may reflect a global reduction in the salience threshold such that all stimulus features are equally more likely to capture attention (See Figure 1) or the threshold may continuously vary either randomly or systematically for different stimulus features.

a)



b)

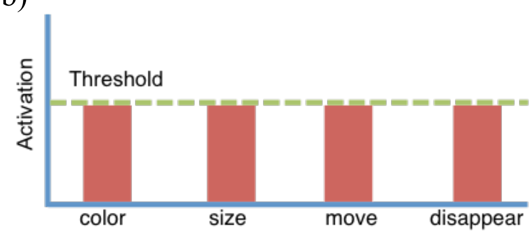


Figure 1 Two attention tuning mechanisms.
Two alternative mechanisms of how attentional tuning can generate a diffuse pattern of attention. (a) depicts a fixed threshold and different change dimensions which are serially activated. Dimensions with more activation and thus closer to the response threshold are easier to detect. (b) depicts an overall reduction in the response threshold such that all change dimensions are equally close and thus equally likely to be detected

Because of their reduced ability to control their attention, lower WM individuals may have a natural propensity to this diffuse state. Put another way, reduced attention control may result in a propensity to exhibit detuned attention or an inability to maintain an attentionally tuned state. However, as with lower WM, this diffusion of attention however it may manifest itself is not necessarily adaptive. Diffuse attention could also easily be characterized as a distracted or mind-wandering state. Thus, there may exist a separate ability responsible for diffusing the attentional system in such a way that is still adaptive and goal focused.

Cognitive Flexibility

One cognitive ability specifically associated with adaptive mental set shifting is cognitive flexibility (CF; Scott, 1962; Ionescu, 2013). CF is defined as the propensity for an individual to abandon one cognitive strategy in favor of another based on a change in task demands (Scott, 1962). CF is often studied in neuropsychological contexts, because the behaviors that arise in its absence, e.g. perseveration, which are often a hallmark of executive dysfunction (Miyake et al., 2000). However, considerable variation has been shown among healthy populations as well (Gonzalez, Figueroa, Bellows, Rhodes & Youmans, 2012). In addition, CF appears to be a separate individual difference from WM as few studies have reported reliable predictive relationships between tasks the Automated Operation Span Task (AOSPAN) and the Wisconsin Card Sorting Task (WCST), a classic measure of CF (Miyake et al., 2000). CF may represent a critical individual difference to include in models of observer characteristics explaining differential rates of change blindness. Specifically, CF may be responsible for adaptively detuning the attentional capture system to accommodate shifts in changing stimulus. In addition, it is important to stress that CF is also considered a reactive ability, that is to say flexible behavior is dependent on the observer recognizing that the current attentional set, goal state or strategy is no longer optimal and abandoning it for a more optimal one rather than in response to an experimenter or overt task cue. Because targets and target features in change blindness tasks are not known to observers a priori, the reactive nature of CF makes it a likely candidate for predicting individual differences in change detection performance.

Preliminary Evidence for a CF and Change Blindness relationship

Preliminary evidence for a CF and change blindness relationship comes from Youmans, Figueroa and Kramarova (2011). In one of the few studies to examine individual differences in WM, CF and change blindness, they found a positive predictive relationship between performance on the WCST and change detection time. However, no significant relationship between WM and change blindness was observed. Thus it remains unclear whether previously observed differential noticing rates among observers are due to WM or unobserved differences in CF. Furthermore, Youmans et al. (2011) did not explore a potential interaction between WM and CF that may provide critical explanatory power to the relationship between individual differences in attention and change blindness. Additional unpublished research from our lab has replicated the results in Youmans et al. (2011) with additional measures of CF and WM. In all cases, I observed a positive predictive relationship between CF and change detection, but no covariation with WM.

Local and Global Benefits of CF

Even if ones assumes that there exists a true relationship between CF and change blindness, correlational evidence alone is insufficient to explain the causal mechanisms between the two constructs. Specifically, it is unclear exactly *why* higher CF would yield better change detection accuracy. Broadly, the causal mechanisms could arise from one of two routes or both simultaneously: First, CF may provide benefits within a single trial, which I will define as "local" benefits. Specifically, local benefits would arise for strategic search or processing differences between high and low CF individuals irrespective of overall task knowledge. Second CF may provide benefits incorporating overall task knowledge, which I will define as "global" benefits. Global benefits refer to how CF manifests itself across the entire change blindness task, specifically in regards to varying change types and the presence or absence of additional task knowledge.

Local benefits may manifest themselves as rapid oscillation between different attentional states (Folk et al., 1994) or detuned attentional capture state (vis-à-vis, Smilek et al, 2006; Watson et al., 2010). In addition local and global benefits, CF may reflect observers' ability to manipulate and use the limited contents visual short-term memory (VSTM; Cowan, 2001; Luck & Vogel, 1997). Simons et al. (2002) argues that change blindness occurs due to comparison failures of preserved internal representations, thus it may be that CF provides a greater ease in shifting between pre and post change representations in VSTM.

Predictions and Current Study

If global benefits are solely responsible for the relationship between CF and change blindness, the relationship should only manifest itself when differing change types are present. Specifically, the varying sequence of change types presented in a change blindness task may result in perseveration on previously identified change types. For example, if an observer correctly identifies a color change, then they may find it more difficult to identify a subsequent change in size or movement. Given the role of CF as an ability to shift mental set, CF should reduce or eliminate any perseveration effects. Furthermore, if the relationship between CF and change blindness is contingent upon limited available knowledge about the target object, then providing information about the current target's changing stimulus dimension should also reduce or eliminate the relationship between CF and change blindness. If the effect of CF persists regardless of the presence of global benefits, then perhaps the relationship between CF and change blindness is driven by trial level local benefits or processing differences in VSTM.

If relevant task knowledge is central to the effect of WM then providing information about the target object should strengthen the relationship between WM and change blindness such that high WM individuals should outperform their low WM counterparts. However, if attention control is a hindrance in visual search paradigms, then perhaps low WM individuals will outperform their high WM counterparts when no relevant task knowledge is present – similar to Conway et al. (2001). In addition, the inclusion of secondary memory load may selectively target the performance of high WM individuals. If a passive attentional state is indeed optimal in visual search then a performance benefit should be observed, especially for high WM individuals.

In addition to the main effects of CF and WM predicting change blindness performance, the two constructs, assumed here to be generally independent, may interact. In particular, CF may provide a protective effect in the absence of WM and the absence of tight control over observers' attention. Conversely, CF may aid high WM individuals engaged in inefficient visual search, a finding that would potentially reconcile findings from Colflesh and Wiley's (2013), Watson et al. (2010) and Smilek et al. (2006).

Current study

In this dissertation and the two studies outlined below I will demonstrate 1) individual differences in both CF and WM predict change blindness in basic change blindness paradigm, 2) CF is an individual difference reflecting the ability to control and dynamically shift one's attention dissociable from WM, and 3) CF and WM interact under differing conditions of task knowledge and difficulty.

Study 1 hypotheses

In Study 1 I measured observers WM and CF as well as their performance on change blindness flicker paradigm task. Within the change blindness task I controlled two key variables: 1) I monitored whether or not the current trial's change type matched the previous correctly identified change type and 2) I presented one block of trials with pre-trial cues which informed participants about the changing dimension in the current trial. The design of Study 1 thus yielded four independent variables (IVs): WM, CF, sequence type, and cueing and one dependent variable: accuracy on the change blindness task. Because there were four IVs present in Study 1, the full model predicting accuracy would have included ten individual parameters: four main effects, three two-way interactions, two three-way interaction and one four-way interaction. Rather than examining the full model containing all possible IV combinations, I tested a series of models of specific subsets pertaining to pre-specified hypotheses.

First, in order to isolate the potential local benefits of CF I conducted an analysis of CF and WM predicting accuracy on the first ten trials of the change blindness task, which contained no cues and the same change type. H1: If CF provides local benefits to change detection, then I should observe a positive predictive relationship between CF and accuracy in the first ten trials.

The remaining hypotheses apply to trials 11 – 64 wherein trials varied in the change type and cueing. H2: In accordance with previous findings (Youmans et al., 2011) CF should exhibit a positive predictive relationship with change detection.

H3: In accordance with previous findings regarding the ability of observers to actively tune their attentional capture system (Folk et al. 1994), participants should perform better on cued trials than uncued trials.

H4: If perseveration on previous change types exists, then trial sequences where the current change type matches the most recently correctly identified change type (non-switch sequences) should have higher accuracy than trial sequences where the current change type differs from the previously identified change type (switch sequences).

H5: If the effect of perseveration of change types exists, then it should be modulated by the presence or absence of cues. Specifically, cueing participants about what the current change type is should reduce or eliminate differences between switch sequence types and non-switch sequence types.

H6: If the effect of perseveration of change types exists, then it should be modulated by an individual's level of CF. Specifically, individuals higher in CF should be better able to overcome perseveration and thus CF should reduce or eliminate differences between trials where the current change type is the same or different than the previously correctly identified change.

H7: If CF modulates perseveration effects due to oscillation between different change types, then the effect CF predicting change blindness should be eliminated or reduced when cues are present.

H8: If CF modulates perseveration effects due to oscillation between different change types, then the interaction between CF and sequence type should be eliminated or reduced when cues are present.

H9: If WM is only predictive of change blindness when relevant task knowledge is present, then the effect of WM should be modulated by presence or absence of cues. Specifically, the magnitude of the effect of WM should be greater when cues are present.

H10: If WM is only predictive of change blindness when the scope of attention can adaptively shift, then CF should modulate the effect of WM. Specifically, the magnitude of the effect of WM should increase as CF increases.

H11: If the magnitude of the effect of WM is greater when cues are present and CF modulates the effect of WM, then the magnitude of the CF by WM interaction should be greater when cues are present.

CHAPTER 2: METHOD STUDY 1

Participants

One hundred and seventeen George Mason University undergraduates participated in the study (76% female with an average age of 20.8). Participants volunteered for the study via the George Mason University undergraduate research portal and were awarded class credit for their completion. Fourteen participants (11% of 117) were excluded from the analysis due to failure to meet the distraction criteria of 85% correct math problems for the AOSPAN task. However, this percentage is typical (Unsworth et al., 2005). In addition, one participant did not complete the YCFA due to experimenter error and was excluded. Although the original experimental design called for ninety-six participants, there was disproportionate subject loss in the early cueing condition so six additional participants were run in order to obtain an equal number of participants in both conditions. The final number of participants used for analysis was 102.

Materials and Procedure

Participants completed all tasks in random order on one of two desktop computers with 27-inch monitors placed approximately 24 inches away.

Cognitive Flexibility. CF was measured via the Youmans Cognitive Flexibility Assessment (YCFA; Gonzalez et al., 2012). Participants completed a practice and seven six-switch puzzle trials.

Working Memory. WM was assessed via the Automated Operation Span Task (AOSPAN; Unsworth, Heitz, Schrock & Engle, 2005) and the Reading Span task (RSPAN; Daneman & Carpenter. 1980). Both tasks were presented in the Psychology Experiment Building Language (PEBL; Mueller & Piper, 2014). The RSPAN task was slightly modified from Daneman and Carpenter's (1980) to resemble the OSPAN task more closely. Instead of recalling the last letter of unrelated sentences, participants were presented with sentences that either make sense, e.g. "Roses smell nice." or did not make sense "Oranges live in water." Participants then needed to identify whether the sentence presented made sense or not, after their response a letter was shown and the sequence continued in a fashion identical to the OSPAN task.

Change Blindness. The change blindness task used a flicker paradigm (Rensink et al., 1997) with randomized bubble arrays. The A array was shown for 400ms, followed by a 200ms black masking screen, then the A' array for 400ms, followed once again by the masking screen. Each array contained between 50 and 60 bubbles of varying size and colors. Only one bubble changed per trial. Changes could be in color, movement, disappearance or size. Figure 2 provides an example of a single trial. The first ten trials were of a single change type, color, in order to examine CF benefits prior to requiring global shifts in attentional set between change types. The remaining 54 trials consisted of varying change types. In order to examine perseveration effects, trials were coded as

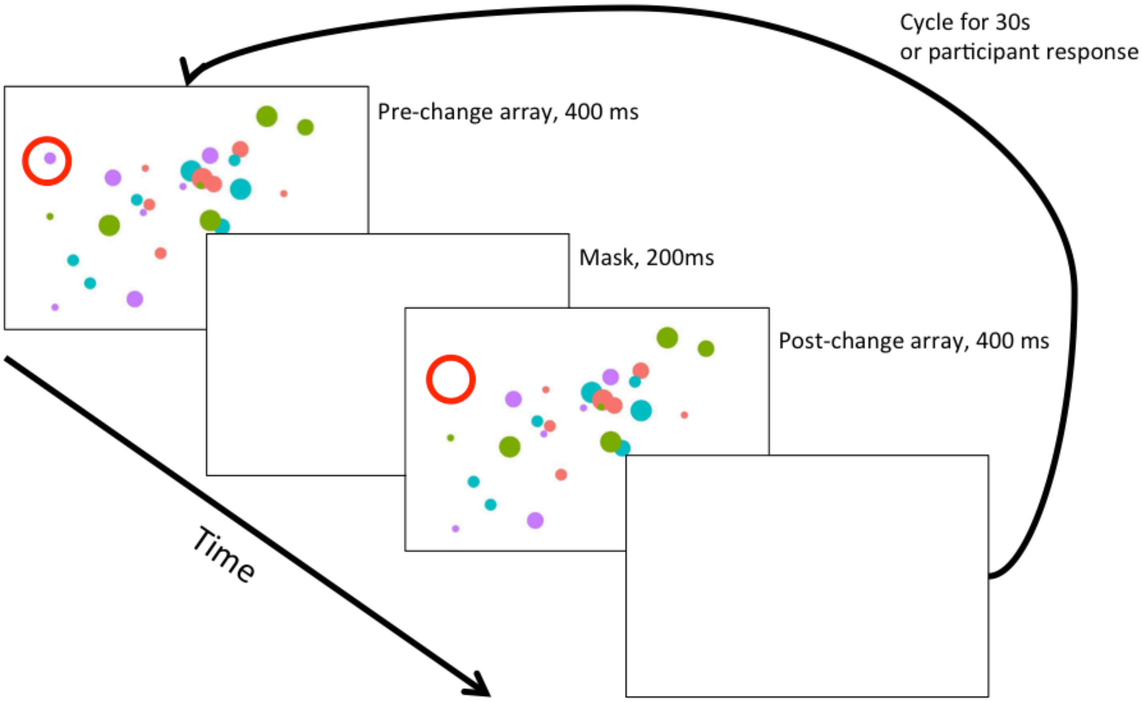


Figure 2 Example change blindness trial.
Example change blindness trial. Changing circle (disappearing) is highlighted in red.

either a switch (S) or non-switch (NS) depending on whether or not the current trial's change type matched the change type of the last correctly identified trial. Participants had 30 seconds to respond to whether they have found the change by pressing the space bar, then localize via a mouse click. During 27 of the final 54 trials participants received valid cues as to what change type is going to occur in the following trial. Cueing trials were presented in counterbalanced blocks so that cue and non-cue blocks occur first and second equally. No feedback accuracy was provided.

CHAPTER 3: RESULTS STUDY 1

Data preparation

AOSPAN task

The AOSPAN task was administered and scored according to Unsworth et al. (2005). Participants Ospan score, the total number of letters recalled in perfectly recalled sets, and total score, the total number of letters recalled, were retained and used for analysis.

RSPAN task

Participants Rspan score, the total number of letters recalled in perfectly recalled sets, and total score, the total number of letters recalled, were retained and used for analysis.

WM composite score

After examining the distributional properties of total span scores from both tasks and well as RSPAN and OSPAN scores, only the respective span scores showed normal distributional properties. In addition, in order to simplify further analysis and capture multiple facets of the working memory capacity construct, a Principal Components Analysis (PCA) was performed in order to reduce the dimensionality of the two span scores to a single composite score. The first principal component retained 70% of the variance of the two scores and displayed correlations near unity with both.

YCFA

The Youmans Cognitive Flexibility Assessment (YCFA) was administered according to Gonzalez et al. (2014). Participants' average switch move time and non-switch move times were first screened for outliers. In order to reduce effects of interruptions or distractions during the task on average times, any times longer than three standard deviations above the mean were removed. The primary measure of cognitive flexibility was a weighted cost score, computed by weighting the ratio of average switch move times to average non-switch times by the square root of average non-switch move times. Weighting by the square root of average non-switch move times was done to penalize low switch cost scores that are typified by longer average non-switch move times rather than faster switch move times. The weighted cost score was z-scored and reverse coded for analysis.

Change blindness task

The first ten trials of the change blindness task were analyzed separately from the main analyses. In addition, any trials with response times shorter than one second were discarded (< 4% of total trials) as this was shorter than the amount of time to actually see a single change. Sequence types were reduced to switch and non-switch in order to reduce the dimensionality of the analyses. Finally, correct responses were averaged across cueing, presentation order and sequence type. Table 1 contains descriptive statistics for all five tasks.

Table 1 Study 1 descriptives.
Ospan and Rspan score represent the total number of recalled letters from perfectly recalled sets of letters in each task. The composite score represents the first principal component of a principal component analysis of both Ospan and Rspan scores. Weighted cost reflects the average switch cost on the YCFA weighted by the square root of average non-switch move times. Accuracy on the change blindness task is the percent correct trials for trials 11 – 64.

	M	SD	Median	Min	Max	Skew	Kurtosis
WM							
Ospan score	36.14	18.06	37	0	77	-0.11	-1.07
Rspan score	68.14	26.29	69.5	9	123	-0.05	-0.63
Composite	0	1.27	0.11	-2.72	2.89	-0.19	-0.74
CF							
Weighted Cost	1.55	0.23	1.54	1.13	2.17	0.4	-0.31
Change Blindness							
Accuracy	0.52	0.22	0.56	0	0.85	-0.67	-0.4

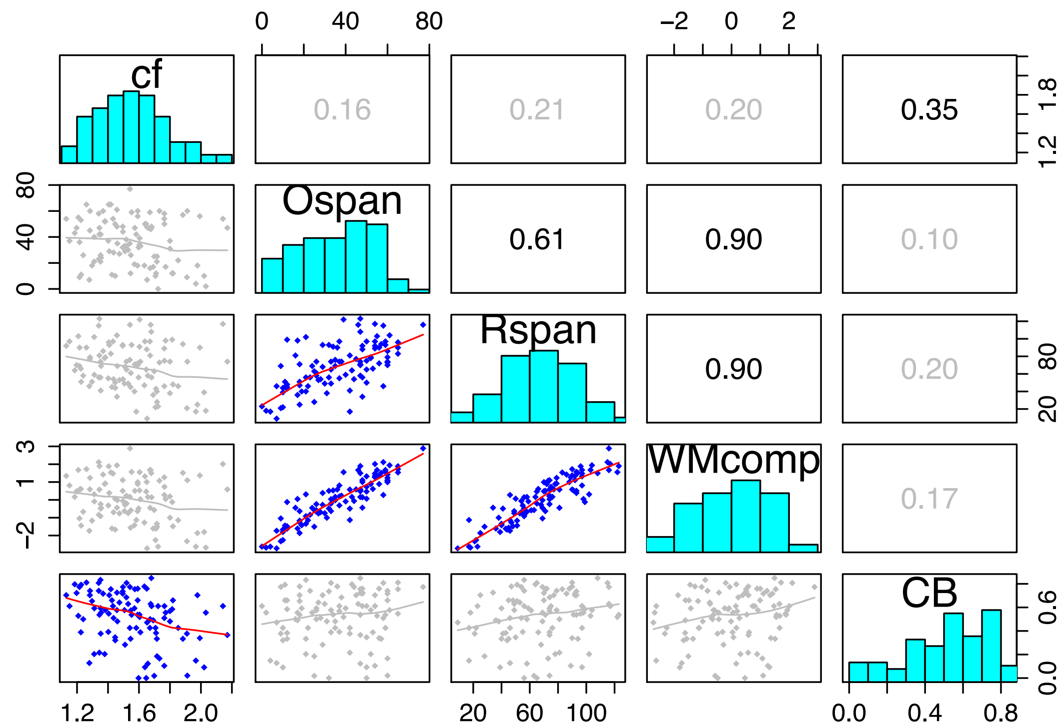


Figure 3 Study 1 correlations.
Matrix of Pearson correlations (upper triangle), histograms (diagonal) and bivariate scatter plots (lower triangle) with smooth lines for all Study 2 tasks. Pearson correlations >.3 are bolded. cf = cognitive flexibility; Ospan = Ospan perfect score; Rspan = Rspan perfect score; WMcomp = WM composite score; CB = overall accuracy on change blindness task.

Analysis approach

In order to test my hypotheses, I used a Bayesian hierarchal mixed effects regression implemented in STAN (STAN Development Team, 2014a), a Hamiltonian Monte Carlo (HMC) sampler, and rstan (STAN Development Team, 2014b). Bayesian data analysis (BDA) offers a conceptually different approach to hypothesis testing than traditional frequentist approaches – otherwise known as Null Hypothesis Significance testing (NHST). For a more detailed review of the differences between BDA and NHST see (Kruschke, 2012, 2010a, 2010b, 2011; Wagenmakers, 2010), but I will summarize their work here. In general NHST is based on assumptions about the sampling distribution of the Null hypothesis, e.g. a t-distribution centered at 0. Data are collected and analyzed based on the researcher's a priori intentions and analysis plan and then p-values are calculated to reflect the probability of observing this, or more extreme, data under the assumption that the Null hypothesis is true. However, this approach is unsatisfactory for several reasons. First, NHST only provides the researcher with a single point estimate of a parameter value ignoring other possible credible estimates.[1] Second, because NHST employs a frequentist approach to probability, the p-values associated with specific point estimates of parameter values are reflective of the probability of observing this, or more extreme data, under the Null hypothesis if the experiment was to be repeated as intended an arbitrarily high number of times. Thus because p-values are directly tied to an experimenter's a priori intentions, it is unclear then how to interpret a p-value if the experimenter collects more or less data than intended or if unexpected data loss occurs (Edwards, Lindman & Savage, 1963; Kruschke, 2010b). Furthermore, the experimenter is "punished" by applying p-value corrections if unplanned comparisons are examined. This is turn leads to an unnecessary increase in Type II error and may motivate researchers to be disingenuous in their stated goals for which comparisons were planned or unplanned in an experiment after examining the data.

[1] Confidence intervals also fail to provide credible estimates as they do not possess distribution properties rather reflective of a range values that would also lead to a rejection of the Null hypothesis (Kruschke, 2010a)

In comparison, BDA does not suffer from any of the conceptual issues outlined above. This is because, instead of relying on a frequentist interpretation of probability (i.e. probability as the long-run frequency of an event), BDA conceptualizes probability as a magnitude of belief that any given event will occur. Most importantly, these beliefs are updated in a systematic manner as evidence, i.e. data, is made available. This process of updating is based fundamentally on Bayes Rule (Bayes & Price, 1763). As Kruschke (2010a) writes:

> *In BDA, the researcher uses a descriptive model that is easily customizable to the specific situation without the computational restrictions in conventional NHST models. Before considering any newly collected data, the analyst specifies the current uncertainty for parameter values, called a prior distribution that is acceptable to a skeptical scientific audience. Then Bayesian inference yields a complete posterior distribution over the conjoint parameter space, which indicates the relative credibility of every possible combination of parameter values. In particular, the posterior distribution reveals complete information about correlations of credible parameter values.*

Thus, I elected to use a Bayesian data analysis (BDA) approach for three main reasons. First, BDA provides richly informative posterior probability distributions that describe reasonable estimates for the parameters of interest. This allows future researchers to interpret related work regardless of intention. Second, because BDA allows the incorporation of prior information I can build a coherent connection between Study 1 and Study 2 by using the posterior distribution of Study 1 as the prior distributions for Study

2. Finally, the absurd and unnecessarily restrictive assumptions of researcher intention related to multiple comparisons are eliminated in BDA. This is because the posterior distribution provides a complete description of all possible combinations of parameter values. Thus, making comparisons between different conditions within the same model are valid regardless of researcher intention. In BDA, the (non) issue of multiple comparisons can be conceptualized as observing the faces of a cube. Only one face is clearly visible to the observer at any given moment, thus in order understand its structure the observer must rotate the cube or change their view. This change in perspective does not alter the object being observed, only the observer's perspective. Similarly, examining comparisons between parameters in BDA does not change the data, parameter estimates or their distributional properties; instead, comparisons reflect changes in the researcher's perspective.

Mechanics of Bayesian Data Analysis and Terminology

Unlike NHST, which relies on assumptions about Null sampling distributions, BDA uses sampling algorithms (Markov chain Monte Carlo methods; MCMC; Metropolis, Rosenbluth, Teller & Teller, 1953; Hastings, 1970) to approximate the posterior distribution of credible values of parameters (e.g. a mean, standard deviation or regression weight) to an arbitrarily high accuracy. The program used here, STAN, differs slightly from traditional MCMC methods in that STAN uses Hamiltonian Monte Carlo (HMC) methods, which transform the problem of sampling from a target posterior distribution of parameter estimates into the problem of simulating Hamiltonian dynamics (Hoffman & Gelman, 2013; Neal, 2011). HMC methods are often more efficient than traditional MCMC methods, but require additional analyst-set tuning parameter to maximize that efficiency. For this reason STAN also implements the No-U-Turn Sampler (NUTS; Hoffman & Gelman, 2013), which adaptively tunes the parameters automatically to minimize convergence time.

Like MCMC, HMC methods use one or more "chains" to sample the joint posterior probability distribution of all the parameters of interest. The chains are composed of typically thousands of representative samples for each parameter (See Figure 4). These chains are then combined and summarized to provide a distribution of credible values for all the parameters of interest.

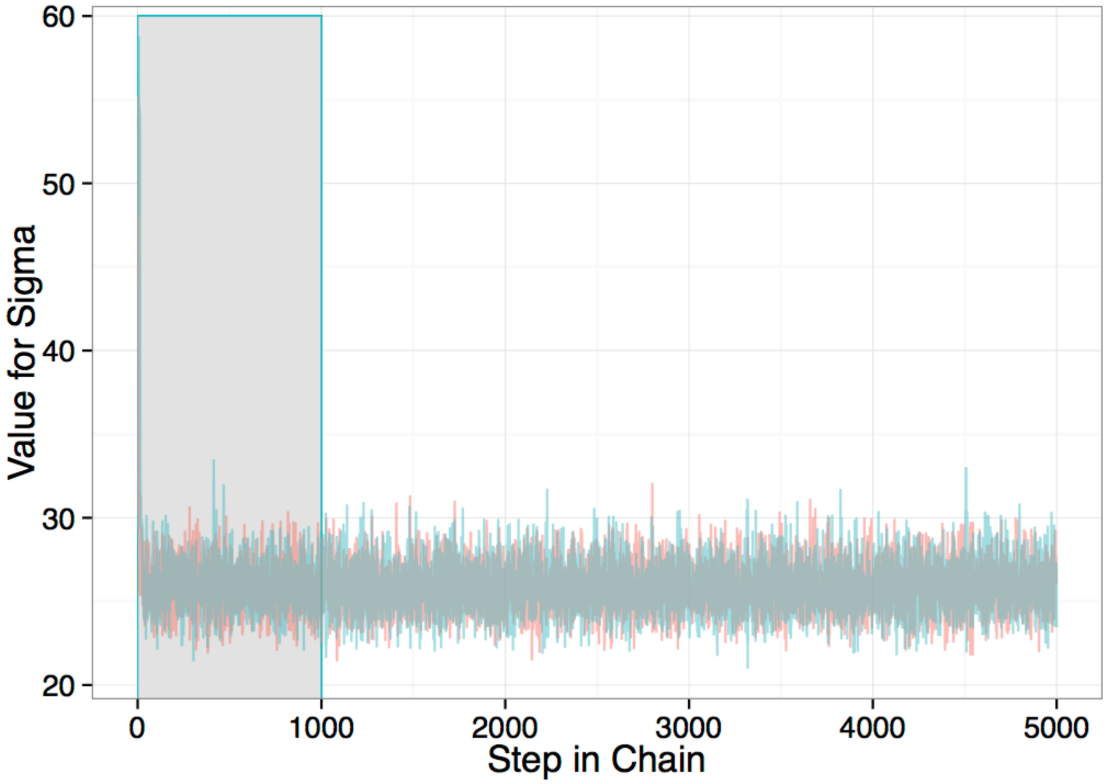


Figure 4 Example MCMC chains
Example of two 5,000-step MCMC chains for the parameter Sigma. Burn-in/warm-up period is shaded.

Furthermore, the mean of the distribution of samples serves as the best point estimate for a parameter. Once summarized, one can assess the magnitude of the effect of a parameter by computing the Highest Density Interval (HDI), which represents the bulk of where credible valuables for any given parameter lie (see Figure 5). For example, a 95% HDI provides a range of values which contains 95% of the credible values for a given parameter. One can then compare this HDI to a value or range of values of interest and determine what percentage falls above, below or within. For example, if one assumes the value of Sigma in Figure 5 is a regression coefficient, and one is interested in determining if 21 is a credible value, one can simply compute what proportion of the sample of parameter estimates are less than or equal to 21. For Null values, like 0 for a regression coefficient or 21 in our example, Kruschke (2011; 2010a) suggests establishing a Region of Practical Equivalence (ROPE), which defines a range of values centered around the Null value that can be considered “practically equivalent” to the Null. Thus, even if a 95% HDI doesn’t contain the exact Null value, if the HDI contains values that are practically equivalent to the Null one must still consider the Null as a potentially credible value for our parameter.

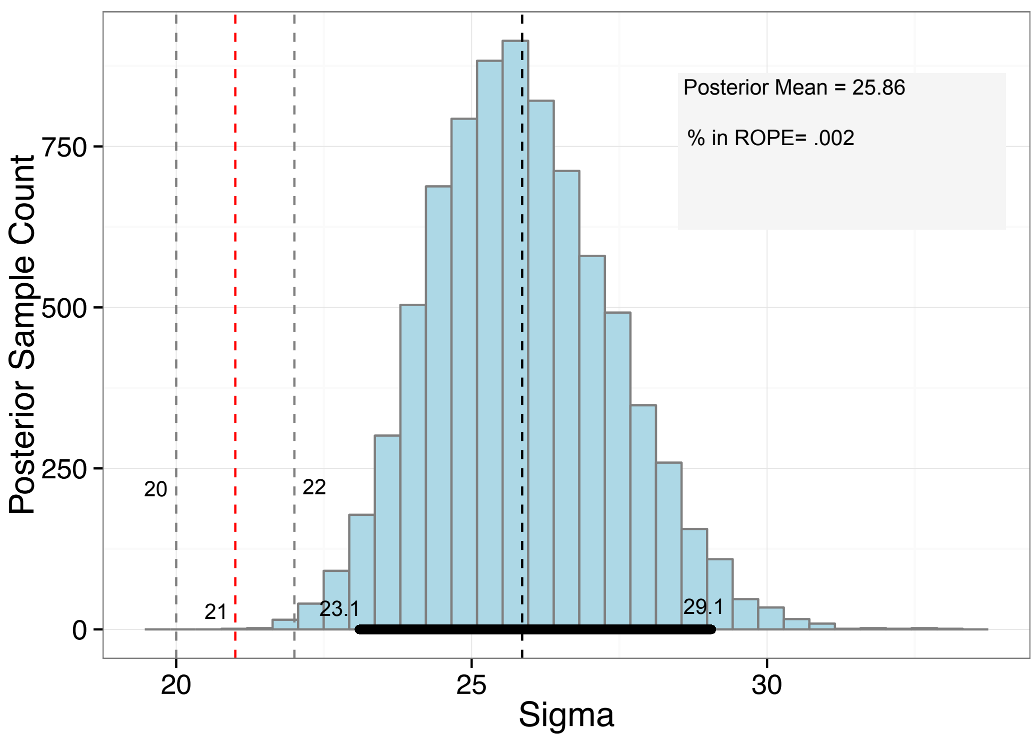


Figure 5 Example histogram of MCMC samples.
Example histogram of posterior samples of Sigma drawn from chains in Figure 4. 95% HDI is shown in black at the base of the plot. Null value of 21 and ROPE of 20 – 22 is shown to the left.

In conclusion, BDA provides an analyst with a set of tools to estimate credible values for parameters of interest. MCMC/HMC methods yield a large number of representative samples of credible values for parameter estimates based on the data and the summary statistics and precision of this distribution of samples can be used to assess the credibility of Null (or any other) values in a manner similar to the decision making logic of NHST. The ROPE adds an additional level of control and conservativeness that makes it more difficult to reject Null values if values that are practically equivalent to the Null are included within the HDI.

MCMC/HMC Diagnostics

Because the interpretability of the posterior distribution approximated from samples from MCMC/HMC algorithms, it is important to ensure the chains are representative of the target distribution and stable or converged (Kruschke, 2010a). In order to ensure that unrepresentative samples are not included in the final posterior distribution, a burn-in or warm-up period is often used (Figure 3.3), wherein unrepresentative samples as the chains attempt to stabilize to the target distribution are omitted from the final sample. In addition to a visual inspection of the chain as in Figure 3.3 above, numerous convergence statistics are available. The Gelman-Rubin (Gelman & Rubin, 1992) statistic, $\hat{R}$, provides an estimate of the potential scale reduction caused by unconverged chains. In general, $\hat{R}$ values equal to 1 suggest convergence while values greater than 1.1 suggest that more samples would be required to ensure the chain has converged. Finally, because each step in the sampling chain is in part dependent on the previous step chains often have a high degree of autocorrelation. This autocorrelation reduces the information gained from each individual sample and may increase estimation error. In order to determine the influence of autocorrelation, effective sample size (ESS or Neff) is often monitored to ensure that autocorrelation has not severely reduced the representativeness of our sample.

Choice of prior

I used uninformative, "flat" normally distributed priors (M=0, SD=10) for all parameter estimates. The extremely wide prior distribution centered around zero reflects our knowledge about the parameter estimates in this study. Essentially an uninformative prior suggests that almost any effect size from extremely large positive or negative to small is credible.

MCMC Methods

All parameters in Study 1 were sampled via HMC/NUTS (Hoffman & Gelman, 2011) with four 6,000 step, un-thinned chains and a 1,000 step warm-up period for a total sample size of 20,000 post warm-up. Effective sample size and scale reduction were monitored for all parameters.

WAIC and Bayesian Model Comparison

After fitting a Bayesian model it is common to compute some estimate of model fit for purposes of model comparison. In frequentist models the Akaike Information Criterion (AIC) measures the degree of model fit correcting for the number of parameters and is often used to compare and select competing models (Akiake, 1973). The

Watanabe-Akaike or widely applicable information criterion (WAIC; Watanabe, 2010), is a fully Bayesian measure of model fit that can be used similar to AIC to compare the goodness-of-fit of competing models accounting for additional complexity of adding additional parameters. The WAIC has also been shown to be comparable to more computationally intensive cross-validation techniques (Vehtari & Gelman, 2014). In general, given two competing models the model with the smaller WAIC value indicates a better fit to the data.

Mixed Effects Regression

I used linear mixed effects regression with fixed and random effects as my primary modeling tool. In addition to my fixed effects, which represent the primary parameters of interest, various random effects are often included to account for nuisance variables and nested data, like trials nested within subjects. Random effects can include random intercepts as well as slopes. Random intercepts allow the average value of the dependent variable to vary between groups, but maintain the effect of the independent variable as fixed. Random slopes allow the magnitude of an effect to vary. For my purposes, only models with random intercepts were considered. Using random intercepts allowed me to account for the split-plot nature of the experimental design (Fisher, 1925; Box & Jones, 1992). Study 1 and 2 would be considered split-plot designs due to the fact that I had only one observation of CF and WM per participant, but multiple observations of cueing and sequence type. Random subject intercepts account for the nested structure of the data and allow me to examine between and within subjects interactions.

ROPE and Significance

I determined whether a parameter was a significant predictor in the model by examining two criteria: 1) whether the 95% HDI included 0 and 2) whether the percent of samples in the ROPE was less than 5%. Although the criteria for the ROPE vary from domain to domain, I chose to set my ROPE as +/- .05 above/below 0. Because regression coefficients were standardized this translates to a 5% SD increase or decrease in accuracy or a 1% increase or decrease in accuracy based on the observed SD of .26 and .2 in Study 1 and 2 respectively. Thus, a significant effect needed to omit 0 as one of the 95% most credible values and contain less than 5% of its posterior samples in the ROPE. If an effect met one but not both of those criteria, it was considered marginally significant. If an effect failed to meet either criterion, it was considered non-significant. It is important to note this criterion is actually *more* conservative than traditional frequentist hypothesis testing inasmuch as a frequentist test can reach significance as long as the boundaries of the confidence interval do not cross zero (or whatever the Null value is) even if the boundaries are practically equivalent, e.g. a significant effect with 95% confidence interval of .000001 and .1 is still statistically significant , while a CI of -.0000001 and .09 would fail to reach significance.

Variable Names for Study 1 Models

In order to aid interpretation of subsequent models and results the Table 2 includes the names and abbreviations for all fixed and random effects used in models in Study 1.

Table 2 Variable names and descriptions for Study 1 models.

Variable		Abbreviation	Description	Type	Ref level
Dependent	Accuracy	acc	average correctly identified changes	continuous, scaled	NA
Fixed Effects	Working Memory Capacity	wm	Composite working memory capacity score	continuous, scaled	NA
	Cognitive Flexibility	cf	weighted cost, reverse coded	continuous, scaled	NA
	Change Sequence Type	seqtype	Whether the trial was a switch or non-switch (S and NS)	categorical	S
	Cue	cue	Whether a cue was present or not (cue and noCue)	categorical	noCue
	Combined Cue and presentation order	cueComb	noCue_early = uncued trials 11 – 38 noCue_late = uncued trials 39 - 64 Cue_early = cued trials 11 – 38 Cue_late = cued trials 39 - 64	Categorical	noCue _early
Random Effects					
	Participant number	Subject	Participant number	categorical	NA
	Cue presentation order	cueCond	Whether cueing was presented in the first or second block	categorical	Late

Local CF effects: First 10 trials

In order to examine the potential local benefits of CF (H1), i.e. the relationship between and change detection when no global task information is available, I subset data from the first 10 trials, which contained no cues and only color changes. I then submitted the data to a simple regression with fixed effects for WM and CF and their interaction. Table 3 shows the model output for the first ten trials. I found a significant effect of CF predicting change detection accuracy for the first ten trials. The effect was such that for a one standard deviation increase in CF change blindness accuracy increased by 5%.

Table 3 Regression model output for trials 1 - 10, Study 1.
Significant predictors in bold. M and SD represent the average and standard deviation of posterior sample estimates for each parameter. LL and UL represent the upper and lower bounds of the 95% HDI. b is unstandardized effect of each parameter in percent. Model run in STAN with four 6,000-step chains and a 1,000 step burn in period. Rˆ< 1.1 indicates good convergence. Neff reflects effective sample size.

Parameter	M	SD	LL	UL	*b*	% in ROPE	Neff	$\hat{R}$
Fixed Effects								
(Intercept)	-0.01	0.1	-0.21	0.18	0.00		14635	1
cf	**0.22**	**0.1**	**0.02**	**0.42**	**0.06**	**0.04**	**12595**	**1**
wm	0.07	0.11	-0.14	0.28	0.02	0.28	13587	1
cf_X_wm	0.08	0.09	-0.1	0.26	0.02	0.30	13430	1
sigma	0.99	0.07	0.87	1.15	0.26		14322	
WAIC	292							

Global Effects: Trials 11 - 64

Model 1

The remaining analyses will focus on trials 11- 64 which varied in change type and cueing. First I tested a specific set of theoretically motivated fixed main effects and interactions corresponding to hypotheses H2 – H11. In addition, I included random intercepts for participant number and cue presentation order.

In support of H2, I found a significant effect of CF predicting change detection accuracy in Model 1(Table 4). The effect was such that for a one standard deviation increase in CF, accuracy increased by 7%. This estimate reflects the effect of CF for uncued switch trials averaging over cueing order and change types accounting for between subject variability. I identified no other significant main effects or interactions in support of H3 – H10. However, the cueCond random effect exhibited considerable variability suggesting perhaps that cue order was not best modeled as a random effect, i.e. the effect of getting cued late was not exchangeable with getting cued early. Thus in Model 2, I included cueCond as a fixed effect in order to explore potential higher level interactions between cueing, presentation order, and other independent variables.

Table 4 Regression Model 1 output for trials 11 - 64, Study 1.
Significant predictors in bold. M and SD represent the average and standard deviation of posterior sample estimates for each parameter. LL and UL represent the upper and lower bounds of the 95% HDI. *b* is unstandardized effect of each parameter in percent. Model run in STAN with four 6,000-step chains and a 1,000 step burn in period. $\widehat{R}$ < 1.1 indicates good convergence. Neff reflects effective sample size.

Parameter	M	SD	LL	UL	*b*	% in ROPE	Neff	Rhat
Fixed Effects								
(Intercept)	-0.21	4.11	-10.35	9.33	-0.06		2052	1
cf	**0.25**	**0.1**	**0.06**	**0.44**	**0.07**	**0.02**	**5583**	1
wm	0.06	0.09	-0.12	0.23	0.02	0.357	4832	1
seqtypeNS	0.19	0.1	-0.01	0.38	0.05	0.081	11195	1
cueCue	-0.04	0.1	-0.23	0.16	-0.01	0.361	11375	1
cf_X_wm	0	0.08	-0.16	0.15	0.00	0.475	5196	1
cf_X_seqtypeNS	0.11	0.1	-0.09	0.31	0.03	0.224	9580	1
wm_X_cueCue	0.02	0.08	-0.13	0.16	0.01	0.482	16525	1
cf_X_cueCue	0.02	0.1	-0.18	0.22	0.01	0.374	9494	1
seqtypeNS_X_cueCue	0.08	0.14	-0.19	0.36	0.02	0.234	9634	1
cf_X_wm_X_cueCue	0.1	0.07	-0.03	0.23	0.03	0.22	15871	1
cf_X_seqtypeNS_X_cueCue	-0.14	0.14	-0.42	0.14	-0.04	0.178	8593	1
sigma	0.7	0.03	0.65	0.76	0.18		12513	1
Random Effects	Var	SE						
Subject	0.66	0.06					9344	1
cueCond	7.48	13.31					4003	1
WAIC 943								

Model 2

Comparison of the WAIC between Model 1 and Model 2 suggests the inclusion of cueCond as a fixed effect improved overall model fit. In Model 2 once again I found support for H2 via a significant effect of CF predicting change detection. The effect was slightly larger than in Model 1, such that for a one standard deviation increase in CF, accuracy increased by 7%. This estimate reflects the effect of CF for uncued switch trials when cues were presented late, i.e. in the second half of trials. In addition, I found a significant cue x cueCond interaction such that the effect of cueing was reduced by 13% when cues were presented early compared to late. This effect in conjunction with the marginally significant main effect of cueing provides partial support for H3.

In partial support of H8, the effect of WM interacted with cueing and presentation order such that the magnitude of the WM x cue interaction, though not significant in this model, is reversed when cues are presented early rather than late. I also found a significant four-way interaction between WM, CF, cueing and presentation order such that the WM x CF interaction depended both cueing and presentation order providing support for H11. In order to aid interpretation of the high level interactions I visualized the results of Model 2 in Figure 3.5.

Table 5 Regression Model 2 output for trials 11 - 64, Study 1.
Significant predictors in bold. M and SD represent the average and standard deviation of posterior sample estimates for each parameter. LL and UL represent the upper and lower bounds of the 95% HDI. *b* is unstandardized effect of each parameter in percent. Model run in STAN with four 6,000-step chains and a 1,000 step burn in period. $\hat{R}$ < 1.1 indicates good convergence. Neff reflects effective sample size

Parameter	M	SD	LL	UL	*b*	% in ROPE	Neff	$\hat{R}$
Fixed Effects								
(Intercept)	-0.45	0.14	-0.72	-0.18	-0.10		5564	1
cf	**0.31**	**0.13**	**0.05**	**0.58**	**0.07**	**0.02**	**6223**	**1**
wm	0.02	0.12	-0.22	0.25	0.00	0.328	6664	1
seqtypeNS	0.11	0.14	-0.17	0.39	0.02	0.208	7922	1
cueCue	0.26	0.14	-0.01	0.53	0.06	0.055	8580	1
cuecondearly	**0.62**	**0.19**	**0.24**	**1**	**0.14**	**0.002**	**5415**	**1**
cueCue_X_cuecondearly	**-0.59**	**0.19**	**-0.97**	**-0.21**	**-0.13**	**0.002**	**8463**	**1**
cf_X_wm	0.13	0.11	-0.08	0.34	0.03	0.177	6834	1
cf_X_seqtypeNS	0.17	0.14	-0.1	0.43	0.04	0.142	10050	1
wm_X_cueCue	0.15	0.1	-0.04	0.34	0.03	0.14	15663	1
wm_X_cuecondearly	0.07	0.18	-0.29	0.42	0.02	0.203	6442	1
cf_X_cueCue	0	0.13	-0.26	0.26	0.00	0.292	9122	1
cf_X_cuecondearly	-0.14	0.19	-0.52	0.24	-0.03	0.152	6350	1
seqtypeNS_X_cueCue	0.05	0.2	-0.33	0.44	0.01	0.194	7857	1
seqtypeNS_X_cuecondearly	0.1	0.2	-0.28	0.49	0.02	0.172	8208	1
wm_X_cueCue_X_cuecondearly	**-0.34**	**0.15**	**-0.63**	**-0.04**	**-0.07**	**0.023**	**20000**	**1**
cf_X_cueCue_X_cuecondearly	0.02	0.2	-0.36	0.42	0.00	0.203	9771	1
seqtypeNS_X_cueCue_X_cuecondearly	0.1	0.27	-0.43	0.64	0.02	0.137	7679	1
cf_X_wm_X_cueCue	0.13	0.09	-0.05	0.3	0.03	0.173	20000	1
cf_X_seqtypeNS_X_cueCue	-0.22	0.19	-0.59	0.15	-0.05	0.108	9169	1
cf_X_wm_X_cuenoCue_X_cuecondearly	-0.26	0.16	-0.57	0.05	-0.06	0.068	6352	1
cf_X_wm_X_cueCue_X_cuecondearly	**-0.4**	**0.15**	**-0.7**	**-0.09**	**-0.09**	**0.01**	**6931**	**1**
cf_X_seqtypeNS_X_cuenoCue_X_cuecondearly	-0.1	0.2	-0.49	0.28	-0.02	0.176	10759	1
cf_X_seqtypeNS_X_cueCue_X_cuecondearly	0.04	0.19	-0.35	0.42	0.01	0.198	20000	1
sigma	0.68	0.03	0.63	0.74	0.15		20000	1
	Var	SE						
Random Effects								
Subject	0.66	0.06					13579	1

WAIC 929

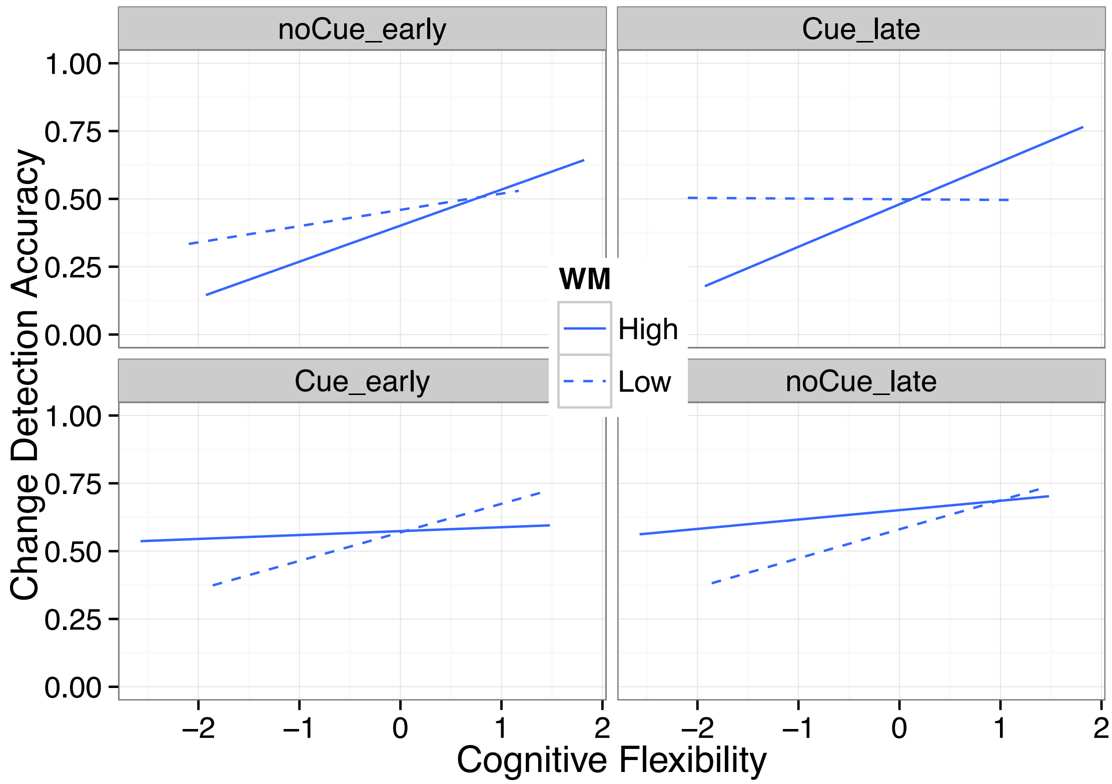


Figure 6 Four-way WM x CF x cue x cueCond interaction.
High and Low WM indicates individuals in the top and bottom 33%, individuals in the middle 33% are not shown. CF is scaled and centered

Figure 6 depicts the interaction between WM and CF for each level of cueing and cueCond. In general, Figure 6 suggests that the WM by CF interaction appears strongest in the noCue_early and the Cue_late conditions. Thus, these particular conditions may be the source of the significant four-way interaction in Model 2. However, although the four-way interaction was significant the main effect of cueCond and the interactions between cueCond and the other IVs were not of interest. Instead the effects of cueCond are only relevant in the conjunction with the effect of cueing. Thus in order to make more explicit comparisons of the cue effects, I created a new variable, cueComb, by combining the levels of cueing, cue and no cue, with the levels of cueCond, early and late, generating a single factor with four levels rather than two, two-level factors. In Model 3, I re ran the analysis in Model 2 with cueComb as independent variable instead of cueing and cueCond.

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Model 3

Inspection of the WAIC between Models 2 and 3 suggest that parameterization of cueing and presentation order as a single factor did not adversely affect model fit. Model 3 yielded a significant effect of CF of the same direction and magnitude as Model 2. Results from Model 3 indicated that participants performed significantly better when cues were presented late compared to early uncued trials providing partial support for H8. However, the difference between early cued trials and early uncued trials, though in the same direction was not significant. As suggested by the significant two-way interaction between cueing and cueCond in Model 2, the magnitude of the effect of cueing appears contingent on when cues were presented in the task.

Finally, marginally significant three-way interactions suggested that the WM x CF interaction was stronger in late cued trials but significantly reduced in early cued trials and late uncued trials providing partial support for H9 and H10. In order to explore these differences I re ran the model in Model 3 with cue_late as the reference level in Model 4.

Table 6 Regression Model 3 output for trials 11 - 64, Study 1.
Cuecond collapsed with cueing into cueComb. Significant predictors in bold. M and SD represent the average and standard deviation of posterior sample estimates for each parameter. LL and UL represent the upper and lower bounds of the 95% HDI. *b* is unstandardized effect of each parameter in percent. Model run in STAN with four 6,000-step chains and a 1,000 step burn in period. $\widehat{R} < 1.1$ indicates good convergence. Neff reflects effective sample size.

Parameter	M	SD	LL	UL	*b*	% in ROPE	Neff	Rhat
Fixed Effects								
(Intercept)	-0.45	0.14	-0.72	-0.18	-0.12		7907	1
cf	**0.31**	**0.13**	**0.05**	**0.58**	**0.08**	**0.020**	**8686**	**1**
wm	0.02	0.12	-0.22	0.25	0.01	0.322	8683	1
seqtypeNS	0.11	0.14	-0.17	0.4	0.03	0.201	10705	1
cueCombCue_early	0.28	0.19	-0.09	0.66	0.07	0.068	8367	1
cueCombCue_late	0.26	0.14	-0.01	0.53	0.07	0.053	20000	1
cueCombnoCue_late	**0.62**	**0.19**	**0.25**	**1**	**0.16**	**0.001**	**8256**	**1**
cf_X_wm	0.13	0.11	-0.08	0.34	0.03	0.183	9249	1
cf_X_seqtypeNS	0.17	0.14	-0.11	0.45	0.04	0.144	11874	1
wm_X_cueCombCue_early	-0.12	0.18	-0.47	0.24	-0.03	0.173	7830	1
wm_X_cueCombCue_late	0.15	0.1	-0.05	0.34	0.04	0.139	20000	1
wm_X_cueCombnoCue_late	0.07	0.18	-0.29	0.43	0.02	0.205	7690	1
cf_X_cueCombCue_early	-0.11	0.19	-0.49	0.27	-0.03	0.174	9254	1
cf_X_cueCombCue_late	0	0.13	-0.26	0.27	0.00	0.292	20000	1
cf_X_cueCombnoCue_late	-0.14	0.19	-0.52	0.24	-0.04	0.158	8570	1
seqtypeNS_X_cueCombCue_early	0.26	0.2	-0.13	0.64	0.07	0.087	13240	1
seqtypeNS_X_cueCombCue_late	0.05	0.2	-0.34	0.43	0.01	0.192	12900	1
seqtypeNS_X_cueCombnoCue_late	0.1	0.2	-0.29	0.49	0.03	0.175	13284	1
cf_X_wm_X_cueCombCue_early	-0.27	0.16	-0.58	0.04	-0.07	0.060	8012	1
cf_X_wm_X_cueCombCue_late	0.13	0.09	-0.05	0.3	0.03	0.168	20000	1
cf_X_wm_X_cueCombnoCue_late	-0.26	0.16	-0.57	0.06	-0.07	0.067	7913	1
cf_X_seqtypeNS_X_cueCombCue_early	-0.18	0.2	-0.58	0.21	-0.05	0.132	15347	1
cf_X_seqtypeNS_X_cueCombCue_late	-0.22	0.19	-0.59	0.16	-0.06	0.108	13795	1
cf_X_seqtypeNS_X_cueCombnoCue_late	-0.1	0.2	-0.49	0.29	-0.03	0.173	15588	1
sigma	0.68	0.03	0.63	0.74	0.18		20000	1
Random Effects	Var	SE						
Subject	0.66	0.06					10962	1
WAIC 929								

Model 4

Given that Models 3 and 4 were identical save for the reference level of cueComb, it follows that the WAIC remained unchanged between the two. Model 4 yielded a significant effect of CF of the same direction and magnitude as Models 2 and 3. In addition, the significant main effects of cueComb support the results of Model 3, such that accuracy was 10% higher for uncued late trials and 7% less for uncued early trials compared to late cued trials.

Model 4 also identified a significant two way interaction between CF and WM such that the magnitude of the effect of CF increases as WM increases. These results supports the interaction observed in Figure 6. However, the significant three-way interactions with cueComb suggest that the magnitude of this interaction was significantly less for cued early trials and uncued late trials.

Table 7 Regression Model 3 output for trials 11 - 64, Study 1.
Cuecond collapsed with cueing into cueComb. Significant predictors in bold. M and SD represent the average and standard deviation of posterior sample estimates for each parameter. LL and UL represent the upper and lower bounds of the 95% HDI. *b* is unstandardized effect of each parameter in percent. Model run in STAN with four 6,000-step chains and a 1,000 step burn in period. $\widehat{R}$ < 1.1 indicates good convergence. Neff reflects effective sample size.

Parameter	M	SD	LL	UL	*b*	% in ROPE	Neff	Rhat
Fixed Effects								
(Intercept)	-0.19	0.14	-0.46	0.08	-0.05		6681	1
cf	**0.31**	**0.13**	**0.05**	**0.57**	**0.08**	**0.020**	**7221**	**1**
wm	0.17	0.12	-0.06	0.4	0.04	0.120	7274	1
seqtypeNS	0.16	0.14	-0.11	0.43	0.04	0.141	10248	1
cueCombnoCue_early	-0.26	0.14	-0.53	0.01	-0.07	0.050	13718	1
cueCombCue_early	0.03	0.19	-0.35	0.41	0.01	0.203	7126	1
cueCombnoCue_late	**0.37**	**0.19**	**-0.02**	**0.74**	**0.10**	**0.030**	**6720**	**1**
cf_X_wm	**0.26**	**0.1**	**0.05**	**0.46**	**0.07**	**0.021**	**7887**	**1**
cf_X_seqtypeNS	-0.05	0.13	-0.31	0.21	-0.01	0.280	10498	1
wm_X_cueCombnoCue_early	-0.15	0.1	-0.34	0.05	-0.04	0.138	20000	1
wm_X_cueCombCue_early	-0.27	0.18	-0.62	0.08	-0.07	0.070	7165	1
wm_X_cueCombnoCue_late	-0.08	0.18	-0.43	0.27	-0.02	0.200	6970	1
cf_X_cueCombnoCue_early	0	0.14	-0.27	0.26	0.00	0.290	12992	1
cf_X_cueCombCue_early	-0.11	0.2	-0.49	0.27	-0.03	0.174	7159	1
cf_X_cueCombnoCue_late	-0.14	0.2	-0.52	0.24	-0.04	0.160	7364	1
seqtypeNS_X_cueCombnoCue_early	-0.05	0.2	-0.43	0.35	-0.01	0.194	12352	1
seqtypeNS_X_cueCombCue_early	0.21	0.19	-0.17	0.59	0.06	0.120	12747	1
seqtypeNS_X_cueCombnoCue_late	0.05	0.19	-0.33	0.42	0.01	0.200	12584	1
cf_X_wm_X_cueCombnoCue_early	-0.13	0.09	-0.3	0.05	-0.03	0.170	20000	1
cf_X_wm_X_cueCombCue_early	**-0.4**	**0.15**	**-0.71**	**-0.1**	**-0.11**	**0.009**	**7876**	**1**
cf_X_wm_X_cueCombnoCue_late	**-0.39**	**0.15**	**-0.69**	**-0.09**	**-0.10**	**0.010**	**7942**	**1**
cf_X_seqtypeNS_X_cueCombnoCue_early	0.21	0.19	-0.16	0.59	0.06	0.115	13002	1
cf_X_seqtypeNS_X_cueCombCue_early	0.03	0.2	-0.35	0.42	0.01	0.200	13609	1
cf_X_seqtypeNS_X_cueCombnoCue_late	0.11	0.19	-0.27	0.5	0.03	0.169	13587	1
sigma	0.68	0.03	0.63	0.74	0.18		20000	1
Random Effects	Var	SE						
Subject	0.66	0.06					10962	1
WAIC 929								

Study 1 Results Summary

Below I summarize the results of Study 1 in regards to the support or lack of support for each of the eleven hypotheses laid out in Chapter 1.

H1: If CF provides local benefits to change detection, then I should observe a positive predictive relationship between CF and accuracy in the first ten trials.

Results from analysis of trials 1 – 10 yielded a significant effect of CF, providing support for H1

H2: In accordance with previous findings (Youmans et al., 2011) CF should exhibit a positive predictive relationship with change detection.

Models 1 – 4 identified a positive predictive relationship between CF and change detection, providing support for H2.

H3: In accordance with previous findings regarding the ability of observers to actively tune their attentional capture system (Folk et al. 1994), participants should perform better on cued trials than uncued trials.

Models 2 – 4 suggested that the effect of cueing was contingent on when cues were presented. When accuracy was higher for cued trials compared to uncued trials when cues were presented late providing support for H3. However, accuracy was higher for uncued trials compared to cued trials when cues were presented early, providing evidence against H3. In addition, the trials with the highest overall accuracy were uncued late trials, providing further evidence against H3.

H4: If perseveration on previous change types exists, then trial sequences where the current change type matches the most recently correctly identified change type (non-switch sequences) should have higher accuracy than trial sequences where the current change type differs from the previously identified change type (switch sequences).

Models 1 – 4 failed to provide evidence in support of H4.

H5: If the effect of perseveration of change types exists, then it should be modulated by the presence or absence of cues. Specifically, cueing participants about what the current change type is should reduce or eliminate differences between switch sequence types and non-switch sequence types.

Models 1 – 4 failed to provide evidence in support of H5.

H6: If the effect of perseveration of change types exists, then it should be modulated by an individual's level of CF. Specifically, individuals higher in CF should be better able to overcome perseveration and thus CF should reduce or eliminate differences between trials where the current change type is the same or different than the previously correctly identified change.

Models 1 – 4 failed to provide evidence in support of H6.

H7: If CF modulates perseveration effects due to oscillation between different change types, then the effect CF predicting change detection should be eliminated or reduced when cues are present.

Models 1 – 4 failed to provide evidence in support of H7.

H8: If CF modulates perseveration effects due to oscillation between different change types, then the interaction between CF and sequence type should be eliminated or reduced when cues are present.

Models 1 – 4 failed to provide evidence in support of H8.

H9: If WM is only predictive of change blindness when relevant task knowledge is present, then the effect of WM should be modulated by presence or absence of cues. Specifically, the magnitude of the effect of WM should be greater when cues are present.

Models 2 identified a significant three-way interaction between WM, cueing and cueing order, providing partial support for H9. However, Models 3 and 4 failed to identify a significant main effect of WM or significant WM by cueCond interaction, providing evidence against H9.

H10: If WM is only predictive of change blindness when the scope of attention can adaptively shift, then CF should modulate the effect of WM. Specifically, the magnitude of the effect of WM should increase as CF increases.

Model 4 identified a significant WM by CF interaction, providing partial support for H10. In addition, the effect was in the predicted direction such that the magnitude of the effect of WM was greater as CF increased. However, this effect was only present in late cued trials providing partial evidence against H10.

H11: If the magnitude of the effect of WM is greater when cues are present and CF modulates the effect of WM, then the magnitude of the CF by WM interaction should be greater when cues are present.

Model 4 identified a significant WM by CF interaction, providing partial support for H11. However, this effect was only present in late cued trials providing partial evidence against H11.

Cue effects and Sequence type

In general, what the pattern of results in Models 3, 4 and 5 suggest is that the effect of cueing is highly dependent on when cues are presented. However, because cues were only presented in either early or late blocks, it is difficult to disentangle the effect of cueing from the effect of time on task. In particular because I identified a significant effect of cueCond in Model 2 this suggests that participants were significantly more accurate during later trials. Despite this, our results suggest evidence of an unforeseen training effect given that cued late trials actually had less accuracy than uncued late trials. Given the evidence of differential transfer, a between-subjects design would be required to examine the pure main effects of cueing across the full duration of the experiment (Gravetter & Wallnau, 2006).

Study 1 failed to find a significant sequence type effect which in turn led to a dearth of evidence in support of interactions between sequence type, cueing and CF. However, it is important to note that because a switch or non-switch trial was determined in part by the participant's performance, the number of switch and non-switch trials was both unequally distributed between participants as well as within. In particular, because there was a only a 1 in 4 chance that the current trial's change dimension would match the previous change trial at random versus a 3 in 4 chance that the change dimensions would not match I observed about twice as many switch moves as non-switch moves. While this observation does not necessarily explain the non-significant effect of sequence type observed in Study 1 it may have made it more difficult to detect smaller effects.

WM, CF and Cueing interaction

Model 2 identified a significant four-way interaction between WM, CF, cueing and cueCond, which Figure 3.5 and Model 3 revealed as being driven predominantly by the WM, by CF interaction when cues were presented late. Although the main effect of cueing was partly confounded by differential transfer effects, the fact that the WM by CF interaction was not significant in late uncued trials suggests that this interaction was indeed dependent on the presence of cues, but only later in the task. Specifically, individuals lower in WM appeared insensitive to differences in CF and maintained consistently mediocre performance when cues were presented late whereas the magnitude of the effect of CF remained intact for high WM individuals. This suggests that high WM individuals can utilize cues by blocking out irrelevant stimulus features, but only if these high WM individuals are also high in CF. When individuals are high in WM but low in CF in the presence of cues they perform worse than their low WM counterparts. This may be interpreted as suggesting that in high WM individuals without high CF, previously relevant now irrelevant cues cannot be abandoned.

CHAPTER 4: DISCUSSION STUDY 1

Based on the results of Study 1, there is evidence to suggest that CF provides local benefits to change detection. First, I found that, even in the first 10 trials of the task where no global task information is available, i.e. cues or perseveration of different change types, higher CF still yielded a significant positive predictive relationship with change detection. Furthermore, in the analysis of trials 11 to 64, I found a robust main effect of CF that remained reliable in the presence of other global task variables. In particular, CF did not interact with sequence type or cueing. This suggests that the benefits of CF to do not, in general, stem from overcoming perseveration from previous change types.

In addition to a main effect of CF, Study 1 also identified a WM by CF interaction during late cued trials. In particular, the effect of CF was reduced as WM decreased. This effect suggests that perhaps CF manifests itself differently in individuals with poor attention control. Specifically, results suggest that low WM individuals may be oscillating between the different changing stimulus dimensions. A behavior which when coupled with high CF yields equivalent performance to their high WM counterparts. However, when cued to the changing stimulus dimension, oscillation between dimensions ceases and thus CF no longer provides a positive effect.

These results help reconcile the contradictory findings observed by Colflesh and Wiley (2013) and Colflesh and Conway (2007). Colflesh and Wiley (2013) found that intoxicated participants found changes more quickly, but exhibited a decrease in performance on the operation span task. Conversely, Colflesh and Conway (2007) found that high WM participants were better at detecting their name in the unattended stream of a dichotic listening task when told to listen for it. In the introduction I suggested that the main difference between these two experiments was the presence of relevant task knowledge. Results from Study 1 suggest that this may be the case, provided that an individual's level of CF is also taken into account. Specifically, Study 1 failed to identify any significant main effect of WM predicting change detection or a significant WM by cueing interaction. However, the form of the WM by CF interaction described in the paragraph above suggests that high WM yields better noticing behavior in the presence of both relevant task knowledge and high CF.

Furthermore, in order to explain the difference between their results and the findings observed by Conway et al. (2001), Conway and Colflesh's (2007) suggested that WM may provide the ability to shift attentional scope in order to meet task demands. However, the significant main effect of CF and the significant CF by WM interaction identified in Study 1 suggest that CF may actually be a separate ability responsible for reactively and adaptively shifting the scope of attention or tuning of the attentional capture system.

In addition to contextual knowledge, real-world change blindness typically occurs in the presence of other tasks in a complex dynamic, environment. For example, drivers may be monitoring the roadway for relevant changes while also engaging in other tasks like conversing with a passenger or talking on the phone. Or an air traffic controller may be communicating with pilots in the air while monitoring flights on a visual display.

Previous work on task load and visual search suggests its effects depend critically on the type of load observers are under while engaging in visual tasks. Specifically, predictions from cognitive load theory (Lavie, 1995; Lavie, Hirst, Fockert & Viding, 2004) demonstrate that when observers are put under high perceptual load, they process task irrelevant distractors less then in low perceptual load conditions. However, distractor processing is increased under cognitive load that taps attentional control processes. According to load theory, high perceptual load depletes attentional resources, leaving observers with no spare resources with which to process distractors. In contrast, when perceptual load is low, leftover attentional capacity “spills over” to distractors resulting in interference. However, when observers are placed under cognitive load by using an additional working-memory task, e.g Lavie et al. (2004), results indicate an increase in interference.

For example, Peterson, Beck & Wong (2008) found that observers took longer to identify the target in a static visual search task during a secondary auditory memory task. In addition, observers had shorter gaze durations and great lag 2 revistations, which suggested that increased cognitive load caused premature shifts in attention. He and McCarley (2010) extended Peterson et al.’s (2008) findings by demonstrating that the effects of cognitive load are independent of perceptual processing effects indicating that the effects of load are specific to executive processes. Finally, Fitousi and Wenger (2011) have argued that perhaps “the effects of cognitive load are not related to changes in the allocation of resources, but to the decrease in an observer’s ability to inhibit their responses to distractors under high cognitive load.” At the aggregate level Fitousi and Wenger (2011) found some support for their reinterpretation, however predictions did not hold equally amongst observers. This suggests that perhaps individual differences in WM, attributed with control via inhibition (Kane & Engle, 2000), and/or differences in CF, attributed with adaptive shifting of attention (Scott, 1962), modulate the impact of load on visual processing.

Only a few studies have applied the predictions of load theory to the phenomenon of change blindness. For example, Lavie (2006) found that when individuals were placed under low perceptual load observers still experienced change blindness and when perceptual load was high the number of correctly detected changes decreased Thus, in contrast to the findings of traditional visual search tasks perceptual load appeared to produce a detriment in performance rather than improvement. Lee, Lee and Boyle (2007) examined the effects of cognitive load on change blindness and found that in a dynamic change blindness task, taking place in a driving simulator, participants were more likely to miss key changes to the driving environment when presented with a secondary auditory memory task. However, similar to Fitousi and Wenger (2011), Lee et al. (2007) also did not measure individual differences. Thus it is unclear how differences in CF and/or WM may have exacerbated or reduced the effect of cognitive load. In addition, the measure of cognitive load used by Lee et al. (2007) required participants to recall the names of restaurants they heard in discrete intervals while driving in a simulated environment. Thus, cognitive load was induced by active maintenance of information in WM, however it is unclear if active monitoring of a continuous secondary task would produce a similar effect.

The goal of Study 2 was to address the gaps in the literature related to the effects of cognitive load on change blindness and explore how individual differences in attention control may moderate these effects. In addition, Study 2 served to partially replicate the results of Study 1, specifically the main effects of CF, WM and sequence type. Cognitive load was manipulated in Study 2 via a continuous monitoring auditory memory task.

Study 2 Hypotheses

In Study 2 I measured observers WM and CF as well as their performance on change blindness flicker paradigm task. Within the change blindness task I controlled two key variables: 1) I monitored whether or not the current trial's change type matched the previous correctly identified change type and 2) I presented one block of trials with secondary memory task presented via headphones. Similar to Study 1, design of Study 2 yielded four main IVs: WM, CF, sequence type, and load and one dependent variable: accuracy on the change blindness task. In addition, performance on the secondary load task was controlled for yielding five total IVs. Similar to Study 1, rather than testing the full set of all possible main effects and high-level interactions, I tested a series of models of specific subsets pertaining to pre-specified hypotheses defined below. Because Study 2 in part served as a replication of Study 1, several hypotheses are identical to Study 1.

First, in order to replicate local benefits of CF, identified in Study 1 I conducted an analysis of CF and WM predicting accuracy on the first ten trials of the change blindness task, which contained no load and the same change type. H1: If CF provides local benefits to change detection, then I should observe a positive predictive relationship between CF and accuracy in the first ten trials.

The remaining hypotheses apply to trials 11 – 64 wherein trials varied in the change type and secondary task load. H2: In accordance with Study 1 CF should exhibit a positive predictive relationship with change detection.

H3: If task load reduces individuals' attention control resulting in increased processing of distractors, then trials without load should have higher accuracy than trials under load.

H4: If perseveration on previous change types exists, then trial sequences where the current change type matches the most recently correctly identified change type (non-switch sequences) should have higher accuracy than trial sequences where the current change type differs from the previously identified change type (switch sequences).

H5: If the effect of perseveration of change types exists, then it should be modulated by the presence or absence of task load. Specifically, task load should increase differences between switch sequence types and non-switch sequence types.

H6: If the effect of perseveration of change types exists, then it should be modulated by an individual's level of CF. Specifically, individuals higher in CF should be better able to overcome perseveration and thus CF should reduce or eliminate differences between trials where the current change type is the same or different than the previously correctly identified change.

H7: If CF modulates perseveration effects due to oscillation between different change types, and the presence of task load increases the differences between sequence types, then the magnitude of the CF by sequence type interaction should be greater under task load.

H8: If CF reflects an individual's ability to shift the scope of attention and task load reduces the control of attention, then the magnitude of the relationship between CF and change detection should be greater under task load.

H9: If WM reflects and individual's ability to control their attention and task load reduces the control of attention, then the magnitude of the relationship between CF and change detection should be greater under task load.

H10: If WM is only predictive of change blindness when the scope of attention can adaptively shift, then CF should modulate the effect of WM. Specifically, the magnitude of the effect of WM should increase as CF increases.

H11: If the magnitude of the effect of WM is greater under task load and CF modulates the effect of WM, then the magnitude of the CF by WM interaction should be greater under task load.

CHAPTER 5: METHOD STUDY 2

Participants

One hundred and forty one George Mason University undergraduates participated in the study (80.5% female with an average age of 19.3). Participants volunteered for the study via the George Mason University undergraduate research portal and were awarded class credit for their completion. Fourteen participants (10% of 141) were excluded from the analysis due to failure to meet the distraction criteria of 85% correct math problems for the AOSPAN task. In addition, one participant did not complete the YCFA due to experimenter error and was excluded. Finally, five additional participants were excluded from the analysis due to failure to perform the secondary task (See data preparation study 2). The final number of participants used for analysis was 121.

Materials and Procedure

Materials and procedures for Study 2 were identical to Study 1, except for two modifications to the change blindness task. First, in order to examine the relationships between CF, WM and CB under dual-task load, I developed an auditory n-back task that was completed concurrently with the change blindness task. Participants received practice and training before completing the modified change blindness task. The auditory task was presented via headphones. Participants heard numbers 1- 4 spoken at a rate of roughly one number every two seconds and whenever a repeat number occurred, participants were required to click the left mouse button. The probability of a repeat was approximately 25%. The auditory task was presented during 27 of the final 54 trials in counterbalanced blocks so that dual and single task blocks occur first and second equally. No feedback was provided and the audio ended whenever the participant pressed the space bar to indicate they had found the change or the trial time limit expired.

CHAPTER 6: RESULTS STUDY 2

Data Preparation

Data preparation and cleaning methods for all tasks were identical to Study 1. In addition, I computed a measure of performance on the secondary auditory task. Because the data collection program only recorded data on trials when at least one click was made, it was not possible to traditional signal detection metrics (e.g. *d*') without knowing the total number of critical signals presented. Instead, I computed a composite score that accounted for both false alarms and non-response. First, I computed the proportion of hits per click. Thus perfect performance would yield a hits-per-click value of 1, indicating no false alarms. Then, in order to account for a conservative bias, i.e. an observer could achieve a hits-per-click value of 1 if they only clicked once and it happened to be a hit, I multiplied the hits-per-click value by the total number of clicks. Thus participants with hit-per-click ratios closer to 1 who clicked often would score higher than more conservative but equally accurate participants or more liberal and less accurate participants. The composite secondary task scores were then log-transformed to normalize the distribution of scores, then standardized. Any participants performing below 3 standard deviations from the mean (N=5) were excluded from the analysis. Descriptive and zero order correlations for all tasks are shown in Table 8and Figure 7

Table 8 Study 2 descriptives.
Ospan and Rspan score represent the total number of recalled letters from perfectly recalled sets of letters in each task. The composite score represents the first principal component of a principal component analysis of both Ospan and Rspan scores. Weighted cost reflects the average switch cost on the YCFA weighted by the square root of average non-switch move times. Accuracy on the change blindness task is the percent correct trials for trials 11 – 64.

Variable	*M*	SD	Median	Min	Max	Skew	Kurtosis
WM							
Ospan score	37.93	19.12	38	2	79	0.06	-1.04
Rspan score	67.79	23.35	66	8	122	-0.03	-0.58
Composite	-0.01	1.33	-0.03	-3.09	3.01	0.07	-0.67
CF							
Weighted Cost	1.53	0.22	1.51	1.08	2.14	0.57	-0.04
CB							
Change Blindness Accuracy	0.55	0.15	0.54	0.02	0.89	-0.48	0.62
Load Task Accuracy	1.23	0.46	1.19	0.33	2.75	0.68	0.71

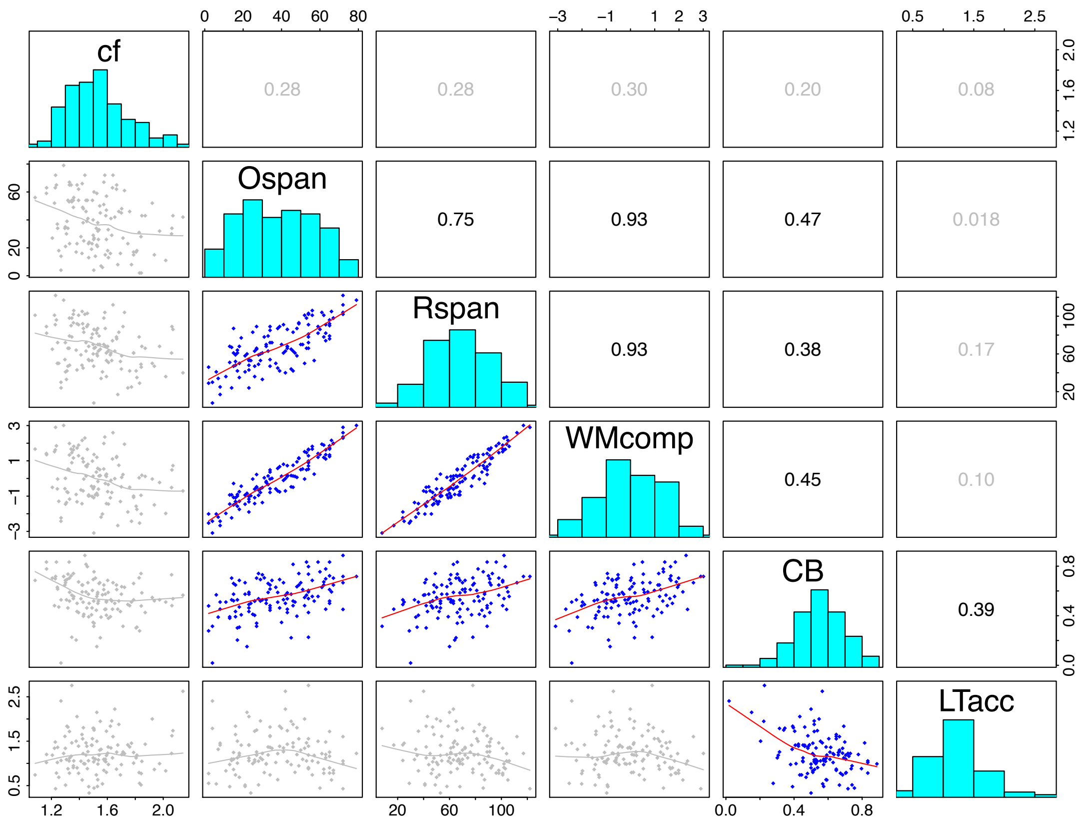

Figure 7 Study 2 correlations.
Matrix of Pearson correlations (upper triangle), histograms (diagonal) and bivariate scatter plots (lower triangle) with smooth lines for all Study 2 tasks. Pearson correlations >.3 are bolded. cf = cognitive flexibility; Ospan = Ospan perfect score; Rspan = Rspan perfect score; WMcomp = WM composite score; CB = overall accuracy on change blindness task; LTacc = overall secondary task accuracy.

Variable Names for Study 2 Models

In order to aid interpretation of subsequent models and results the Table 6.1 includes the names and abbreviations for all fixed and random effects used in models in Study 1.

Table 9 Variable names and descriptions for Study 2.

	Variable	Abbreviation	Description	Type	Reference level
Dependent	Correct detection	corr	Whether change was correctly identified	categorical	Miss
Fixed Effects	Working Memory Capacity	wm	Composite working memory capacity score	continuous, scaled	NA
	Cognitive Flexibility	cf	weighted cost, reverse coded	continuous, scaled	NA
	Load Task Performance	ltacc	Hits-per-click by total clicks, reverse coded	Continuous, scaled	NA
	Change Sequence Type	seqtype	Whether the trial was a switch or non-switch (S and NS)	categorical	S
	Task load	task	Whether a load task was present or not (load and noload)	categorical	noload
	Combined task and presentation order	cueComb	noload_early = no load trials 11 – 38 noload_late = uncued trials 39 - 64 load_early = cued trials 11 – 38 load_late = cued trials 39 - 64	Categorical	noCue_early
Random Effects					
	Participant number	Subject	Participant number	categorical	NA
	Task presentation order	taskCond	Whether load task was presented in the first or second block	categorical	NA
	Trial Number	TrialNumber	Trial Number	categorical	NA
	Change Type	ChangeTypes	Four different change types	categorical	NA

Analysis Approach

Similar to Study 1, I used a Bayesian mixed effects regression in all analyses for Study 2.

Choice of prior

The choice of priors in Study 2 was dictated by the specified models. For parameters not present in Study 1, or parameters present in Study 1 but under conditions that differed from Study 1, I used the same uninformative, "flat" normally distributed priors (M=0, SD=10). When parameters were present under equivalent conditions to Study 1, I used informed priors based on the posterior distributions from Study 1.

MCMC Methods

All parameters in Study 1 were sampled via the No-U-Turn (NUTS) sampler (Hoffman & Gelman, 2011) with four 6,000 step, un-thinned chains and a 1,000 step warm-up period for a total sample size of 20,000 post warm-up.

Local CF effects: First 10 trials

In order to examine the potential local benefits of CF (H1), i.e. the relationship between and change detection when no global task information is available, I subset data from the first 10 trials, which contained no task load and only color changes. Given the similarity between Study 1 and 2 during the first 10 trials, I used the posterior means and standard deviations from Table 3as the priors in Study 2 I then submitted the data to a simple regression with fixed effects for WM and CF and their interaction. Unlike Study 1, I did not find any significant or marginally significant effects. Estimates for all three parameters were near 0. Table 11shows the model results without informed priors for comparison purposes.

Table 10 Regression model output for trials 1 - 10, Study 2.
Priors used for CF, WM and CFxWM are posteriors in Table 3. Significant predictors in bold. M and SD represent the average and standard deviation of posterior sample estimates for each parameter. LL and UL represent the upper and lower bounds of the 95% HDI. *b* is unstandardized effect of each parameter in percent. Model run in STAN with four 6,000-step chains and a 1,000 step burn in period. $\widehat{R}$ < 1.1 indicates good convergence. Neff reflects effective sample size.

Parameter	M	SD	LL	UL	*b*	% in ROPE	Neff	Rhat
Fixed Effects								
(Intercept)	0	0.1	-0.19	0.18	0.00		13547	1
cf	0.09	0.07	-0.05	0.22	0.02	0.27	14249	1
wm	0.02	0.07	-0.12	0.17	0.00	0.55	14486	1
cf_X_wm	0.01	0.07	-0.12	0.14	0.00	0.48	13549	1
sigma	1.02	0.07	0.9	1.17	0.20		13881	1
WAIC	351							

Table 11 Regression model output for trials 1 - 10, no priors, Study 2.
Uninformative priors used for CF, WM and CFxWM. Significant predictors in bold. M and SD represent the average and standard deviation of posterior sample estimates for each parameter. LL and UL represent the upper and lower bounds of the 95% HDI. *b* is unstandardized effect of each parameter in percent. Model run in STAN with four 6,000-step chains and a 1,000 step burn in period. $\widehat{R}$ < 1.1 indicates good convergence. Neff reflects effective sample size.

Parameter	M	SD	LL	UL	*b*	% in ROPE	Neff	Rhat
Fixed Effects								
(Intercept)	0.03	0.1	-0.17	0.22	0.01		12422	1
cf	-0.04	0.1	-0.23	0.15	-0.01	0.36	13760	1
cf_X_wm	-0.1	0.1	-0.29	0.1	-0.02	0.25	11914	1
wm	0.04	0.1	-0.15	0.24	0.01	0.36	12499	1
sigma	1.02	0.07	0.9	1.16	0.20		13253	1
WAIC	352							

Both models with and without priors failed to find significant results. However, the model with priors fit the data slightly better, and provided much tighter posterior estimates. Overall the considerable difference between the effect for first 10 trials of Study 1 and 2 was unexpected. However, I observed a zero-order correlation in Study 2 nearly double that of Study 1. This in turn may have led to greater multicollinearity in Study 2 as exhibited by the moderate correlations between posterior estimates of WM and CF samples[2].

Global Effects: Trials 11 - 64

Model 1

The remaining analyses will focus on trials 11- 64 which varied in change type and task load. First I tested a specific set of theoretically motivated fixed main effects and interactions corresponding to hypotheses H2 – H11. In addition, I included random intercepts for participant number, trial number, change type, and task load presentation order. I used the posterior means and standard deviations from Table 4 for CF, WM, sequence type main effects and for the CF by sequence type interaction and the CF by WM interaction.

[2] In general the increased strength of association between CF and WM may have been due to differences in the sample population between Study 1 and Study 2. In Study 1 participants volunteered near the end of the semester, whereas in Study 2 participants volunteered at the very beginning of the semester. Anecdotally, it has been observed that participants volunteering to participate in experiments at the beginning of the semester may be more motivated than students who delay participation until the end of the semester. Thus the increased correlation between WM and CF in Study 2 may reflect shared variance associated with motivation, i.e. highly motivated participants will perform better on both WM and CF tasks inflating their association.

Table 12 Regression Model 1 output for trials 11 – 64, Study 2.
Priors used for CF, WM, seqtype, CFxseqtype and CFxWM are posteriors in Table 4. Significant predictors in bold. M and SD represent the average and standard deviation of posterior sample estimates for each parameter. LL and UL represent the upper and lower bounds of the 95% HDI. *b* is unstandardized effect of each parameter in percent. Model run in STAN with four 6,000-step chains and a 1,000 step burn in period. $\hat{R}$ < 1.1 indicates good convergence. Neff reflects effective sample size.

Parameter	M	SD	LL	UL	b	% in ROPE	Neff	R
Fixed Effects								
(Intercept)	0.16	3.82	-8.54	10.03	0.03		561	1
cf	0.09	0.06	-0.02	0.21	0.02	0.238	11932	1
wm	**0.19**	**0.05**	**0.08**	**0.3**	**0.04**	**0.006**	**10202**	**1**
seqtypeNS	**0.32**	**0.07**	**0.19**	**0.45**	**0.06**	**0**	**20000**	**1**
taskload	**-0.8**	**0.08**	**-0.96**	**-0.63**	**-0.16**	**0**	**14641**	**1**
ltacc	**0.2**	**0.06**	**0.07**	**0.32**	**0.04**	**0.009**	**6319**	**1**
cf_X_wm	-0.01	0.05	-0.11	0.09	0.00	0.646	12732	1
cf_X_seqtypeNS	0.08	0.07	-0.05	0.2	0.02	0.32	6922	1
wm_X_taskload	0.02	0.06	-0.11	0.15	0.00	0.546	20000	1
cf_X_taskload	0.05	0.08	-0.11	0.21	0.01	0.384	6519	1
seqtypeNS_X_taskload	**0.33**	**0.11**	**0.11**	**0.55**	**0.06**	**0.005**	**13885**	**1**
cf_X_wm_X_taskload	0.14	0.06	0.02	0.27	0.03	0.074	7861	1
cf_X_seqtypeNS_X_taskload	-0.08	0.11	-0.3	0.14	-0.02	0.266	3584	1
sigma	0.69	0.03	0.64	0.75	0.14		12084	1
Random Effects	Var	SE						
Subject	0.5	0.05					2879	1
taskCond	6.01	12.8					1123	1
WAIC 1107								

Model 1 identified a significant effect of WM predicting change detection, such that for a 1 standard deviation increase in WM yielded a 4% in accuracy. In addition, I found a significant effect of sequence type such that participants performed 6% better on non-switch trials. However, this effect interacted with task load, suggesting that the difference between switch and non-switch trials increased under load. In addition, the significant effect of secondary load task accuracy suggests some level of trading off between tasks. Because secondary task performance was reverse coded I can interpret this effect as suggesting that for a one unit decrease in performance on the load task the odds of detecting a change increased by 4%. Finally, I found a significant main effect of task load such that accuracy decreased by 16% under load compared to trials without the secondary task.

Table 13 presents the results of Model 1 with uninformative priors. In general, the results between both models are in close correspondence, however, Model 1 with uninformative priors failed to identify a significant sequence type by task load interaction, identified a small negative effect of CF and a stronger main effect of WM. Despite these differences the WAIC for Model 1 with informative priors was slightly smaller suggesting incorporating prior information from Study 1 provided a better fit to the data.

Table 13 Regression Model 1 output for trials 11 – 64, no priors, Study 2. Uninformative priors used. Significant predictors in bold. M and SD represent the average and standard deviation of posterior sample estimates for each parameter. LL and UL represent the upper and lower bounds of the 95% HDI. *b* is unstandardized effect of each parameter in percent. Model run in STAN with four 6,000-step chains and a 1,000 step burn in period. $\widehat{R}$ < 1.1 indicates good convergence. Neff reflects effective sample size.

Parameter	M	SD	LL	UL	b	% in ROPE	Neff	R
Fixed Effects								
(Intercept)	0.25	3.55	-7.37	9.21	0.05		429	1.01
cf	-0.03	0.08	-0.18	0.13	-0.01	0.444	6385	1
wm	**0.29**	**0.07**	**0.15**	**0.42**	**0.06**	**0.001**	**5968**	**1**
seqtypeNS	**0.43**	**0.09**	**0.25**	**0.6**	**0.08**	**0**	**10084**	**1**
taskload	**-0.75**	**0.09**	**-0.93**	**-0.57**	**-0.15**	**0**	**9774**	**1**
ltacc	**0.21**	**0.06**	**0.08**	**0.33**	**0.04**	**0.006**	**6781**	**1**
cf_X_wm	-0.04	0.07	-0.18	0.09	-0.01	0.444	6213	1
cf_X_seqtypeNS	0.11	0.09	-0.07	0.28	0.02	0.214	8957	1
wm_X_taskload	-0.03	0.07	-0.16	0.1	-0.01	0.506	14855	1
cf_X_taskload	0.12	0.09	-0.07	0.29	0.02	0.201	8042	1
seqtypeNS_X_taskload	0.23	0.13	-0.03	0.48	0.05	0.069	8975	1
cf_X_wm_X_taskload	0.16	0.07	0.03	0.29	0.03	0.054	13077	1
cf_X_seqtypeNS_X_taskload	-0.12	0.13	-0.36	0.13	-0.02	0.21	8290	1
sigma	0.69	0.03	0.64	0.74	0.14		11258	1
Random Effects	Var	SE						
Subject	0.5	0.05					6717	1
taskCond	6.01	12.8					1751	1
WAIC 1108								

Unlike Study 1, Model 1 in Study 2 failed to identify a significant effect of CF. This may have been due to the marginally significant three-way interaction between WM, CF and task load. Alternatively, similar to Model 1 in Study 1, the taskCond random effect exhibited considerable variability suggesting perhaps, like cue order, task order was not truly a random effect. Thus in Model 2 I included taskCond as a fixed effect in order to explore potential higher level interactions between task load, presentation order and other independent variables. In addition, I used posterior means and standard deviations Study 1 Model 2 (Table 5) for CF, WM, and sequence type main effects and for the CF by sequence type interaction and the CF by WM interaction.

Model 2

Model 2 produced slightly different results than Model 1, however the WAIC indicated that including taskCond as a fixed effect fit the data better. Model 2 identified a significant effect of CF as well as a significant CF x taskCond interaction suggesting the null effect identified in Model 1 was due to a reduction of the effect of CF in late trials. In addition, the main effect of sequence type was not significant in Model 2, but sequence type exhibited significant two-way interactions with both task load and presentation order as well as three-way and four-way interactions with CF, task load and presentation order.

Table 14 Regression Model 2 output for trials 11 – 64, Study 2.
taskCond is modeled as a fixed effect. Priors used for CF, WM, seqtype, CFxseqtype and CFxWM are posteriors in Table 5. Significant predictors in bold. M and SD represent the average and standard deviation of posterior sample estimates for each parameter. LL and UL represent the upper and lower bounds of the 95% HDI. *b* is unstandardized effect of each parameter in percent. Model run in STAN with four 6,000-step chains and a 1,000 step burn in period. $\hat{R} < 1.1$ indicates good convergence. Neff reflects effective sample size.

Parameter	M	SD	LL	UL	*b*	% in ROPE	Neff	$\hat{R}$
Fixed Effects								
(Intercept)	0.12	0.11	-0.09	0.32	0.02		10049	1
cf	**0.27**	**0.08**	**0.1**	**0.44**	**0.05**	**0.004**	**13165**	**1**
wm	0.1	0.07	-0.04	0.25	0.02	0.22	14174	1
seqtypeNS	0.2	0.09	0.02	0.38	0.04	0.051	20000	1
taskload	**-0.59**	**0.12**	**-0.83**	**-0.35**	**-0.12**	**0.00**	**13174**	**1**
taskcondearly	-0.07	0.15	-0.37	0.23	-0.01	0.232	10185	1
ltacc	**0.22**	**0.06**	**0.09**	**0.34**	**0.04**	**0.01**	**11692**	**1**
cf_X_seqtypeNS	0.05	0.09	-0.13	0.23	0.01	0.361	20000	1
taskload_X_taskcondearly	-0.29	0.17	-0.63	0.05	-0.06	0.06	12718	1
cf_X_wm	0.05	0.07	-0.1	0.19	0.01	0.423	14356	1
wm_X_taskload	0.11	0.09	-0.07	0.29	0.02	0.21	17595	1
wm_X_taskcondearly	0.23	0.12	0	0.47	0.05	0.055	12556	1
cf_X_taskload	0.04	0.12	-0.2	0.28	0.01	0.29	13133	1
cf_X_taskcondearly	**-0.48**	**0.14**	**-0.75**	**-0.22**	**-0.09**	**0.001**	**11743**	**1**
seqtypeNS_X_taskload	**0.36**	**0.15**	**0.06**	**0.66**	**0.07**	**0.02**	**14622**	**1**
seqtypeNS_X_taskcondearly	**0.4**	**0.15**	**0.09**	**0.7**	**0.08**	**0.01**	**15448**	**1**
wm_X_taskload_X_taskcondearly	-0.19	0.13	-0.45	0.06	-0.04	0.10	17859	1
cf_X_taskload_X_taskcondearly	0.1	0.17	-0.24	0.43	0.02	0.203	12785	1
seqtypeNS_X_taskload_X_taskcondearly	-0.19	0.23	-0.65	0.26	-0.04	0.12	13247	1
cf_X_wm_X_taskload	0.01	0.09	-0.17	0.19	0.00	0.407	20000	1
cf_X_seqtypeNS_X_taskload	**-0.3**	**0.16**	**-0.61**	**0.01**	**-0.06**	**0.04**	**14953**	**1**
cf_X_wm_X_tasknoload_X_taskcondearly	-0.07	0.12	-0.3	0.16	-0.01	0.281	11705	1
cf_X_wm_X_taskload_X_taskcondearly	0.13	0.13	-0.14	0.38	0.03	0.19	12114	1
cf_X_seqtypeNS_X_tasknoload_X_taskcondearly	0.19	0.15	-0.1	0.48	0.04	0.125	20000	1
cf_X_seqtypeNS_X_taskload_X_taskcondearly	**0.45**	**0.17**	**0.1**	**0.79**	**0.09**	**0.01**	**20000**	**1**
	Var	SE						
Random Effects								
Subject	0.66	0.06					13579	1

WAIC	1095

Table 6.7 presents the results of Model 2 with uninformative priors. In general, the results between both Models are in close correspondence, however, Model 2 with uninformative priors failed to identify a significant sequence by task load interaction, identified a smaller non-significant effect of CF, a significan main effect of sequence type, and a stronger, but non-significant main effect of WM. Despite these differences the WAIC for Model 2 with informative priors was slightly smaller suggesting incorporating prior information from Study 1 provided a better fit to the data.

Table 15 Regression Model 2 output for trials 11 – 64, no priors, Study 2.
taskCond is modeled as a fixed effect. Uninformative priors used. Significant predictors in bold. M and SD represent the average and standard deviation of posterior sample estimates for each parameter. LL and UL represent the upper and lower bounds of the 95% HDI. *b* is unstandardized effect of each parameter in percent. Model run in STAN with four 6,000-step chains and a 1,000 step burn in period. $\hat{R}$ < 1.1 indicates good convergence. Neff reflects effective sample size.

Parameter	M	SD	LL	UL	*b*	% in ROPE	Neff	$\hat{R}$
Fixed Effects								
(Intercept)	0.13	0.11	-0.1	0.35	0.03		6352	1
cf	0.24	0.12	0	0.48	0.05	0.051	6400	1
wm	0.19	0.1	-0.01	0.38	0.04	0.074	7133	1
seqtypeNS	**0.27**	**0.12**	**0.02**	**0.51**	**0.05**	**0.034**	**9023**	**1**
taskload	**-0.58**	**0.13**	**-0.83**	**-0.33**	**-0.11**	**0**	**8252**	**1**
taskcondearly	-0.07	0.16	-0.39	0.24	-0.01	0.224	6497	1
ltacc	**0.22**	**0.06**	**0.1**	**0.35**	0.04	**0.004**	**9453**	**1**
cf_X_seqtypeNS	-0.03	0.13	-0.28	0.23	-0.01	0.295	9435	1
taskload_X_taskcondearly	-0.31	0.18	-0.66	0.04	-0.06	0.052	7629	1
cf_X_wm	-0.04	0.1	-0.24	0.15	-0.01	0.356	7268	1
wm_X_taskload	0.07	0.1	-0.12	0.26	0.01	0.307	12753	1
wm_X_taskcondearly	0.15	0.14	-0.12	0.42	0.03	0.162	7714	1
cf_X_taskload	0.04	0.14	-0.23	0.3	0.01	0.278	7833	1
cf_X_taskcondearly	**-0.46**	**0.16**	**-0.78**	**-0.14**	**-0.09**	**0.005**	**6785**	**1**
seqtypeNS_X_taskload	0.29	0.18	-0.05	0.63	0.06	0.061	8672	1
seqtypeNS_X_taskcondearly	**0.33**	**0.18**	**-0.01**	**0.68**	**0.06**	**0.041**	**8277**	**1**
wm_X_taskload_X_taskcondearly	-0.16	0.13	-0.42	0.1	-0.03	0.152	13281	1
cf_X_taskload_X_taskcondearly	0.11	0.18	-0.25	0.46	0.02	0.183	8407	1
seqtypeNS_X_taskload_X_taskcondearly	-0.12	0.25	-0.61	0.36	-0.02	0.148	7540	1
cf_X_wm_X_taskload	0.05	0.1	-0.14	0.24	0.01	0.348	20000	1
cf_X_seqtypeNS_X_taskload	-0.22	0.18	-0.59	0.14	-0.04	0.106	8403	1
cf_X_wm_X_tasknoload_X_taskcondearly	0.01	0.13	-0.25	0.28	0.00	0.294	7589	1
cf_X_wm_X_taskload_X_taskcondearly	0.17	0.13	-0.09	0.43	0.03	0.134	9029	1
cf_X_seqtypeNS_X_tasknoload_X_taskcondearly	0.27	0.17	-0.08	0.61	0.05	0.069	10566	1
cf_X_seqtypeNS_X_taskload_X_taskcondearly	**0.45**	**0.17**	**0.11**	**0.79**	**0.09**	**0.008**	**20000**	**1**

	Var	SE		
Random Effects				
Subject	0.66	0.06	13579	1
WAIC	1097			

I visualized the four-way interaction identified in Model 2 in Figure 8. The figure indicates that early trials not under task load fail to exhibit a main effect of sequence type or a sequence type by CF interaction. However, the interaction for subsequent trials under load suggests that the effect of CF was stronger for switch rather than non-switch trials. Conversely, in trials where task load was presented early and the subsequent trials without dual task load, the interaction is reversed, whereby the effect of CF was strongest for non-switch trials. In addition, Figure 6.4 shows the main effect of sequence type split by task load and presentation order.

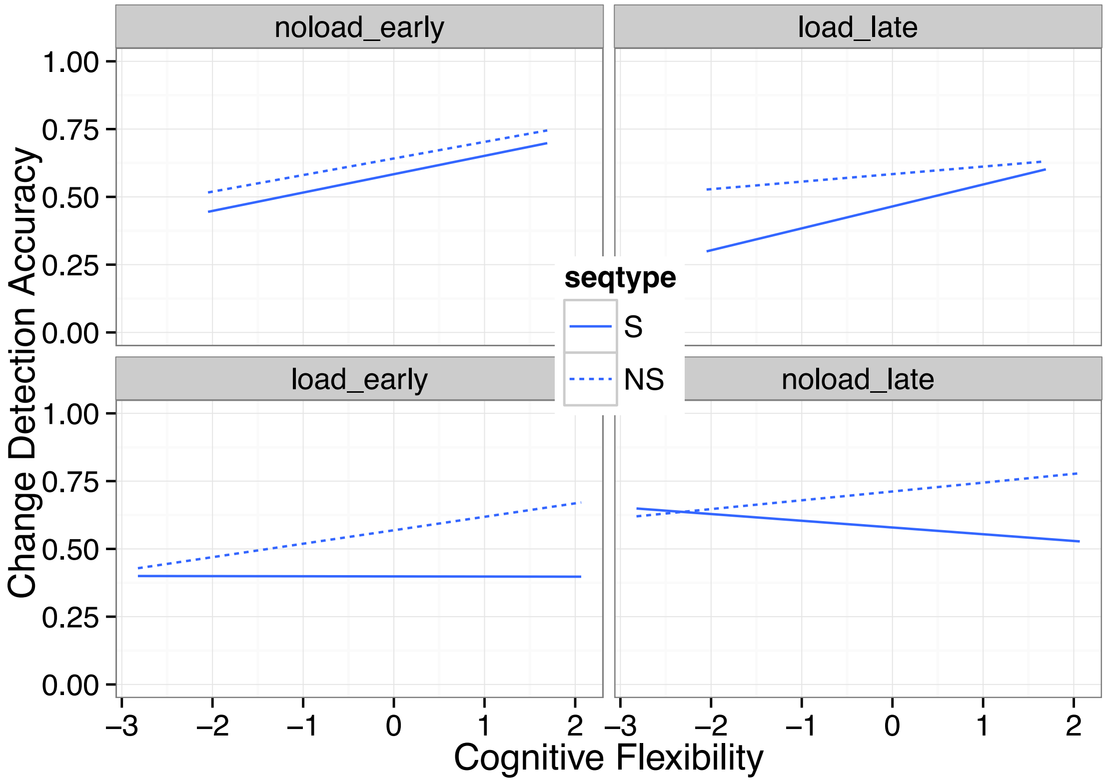

Figure 8 Four-way Sequence type x CF x load x taskCond interaction.

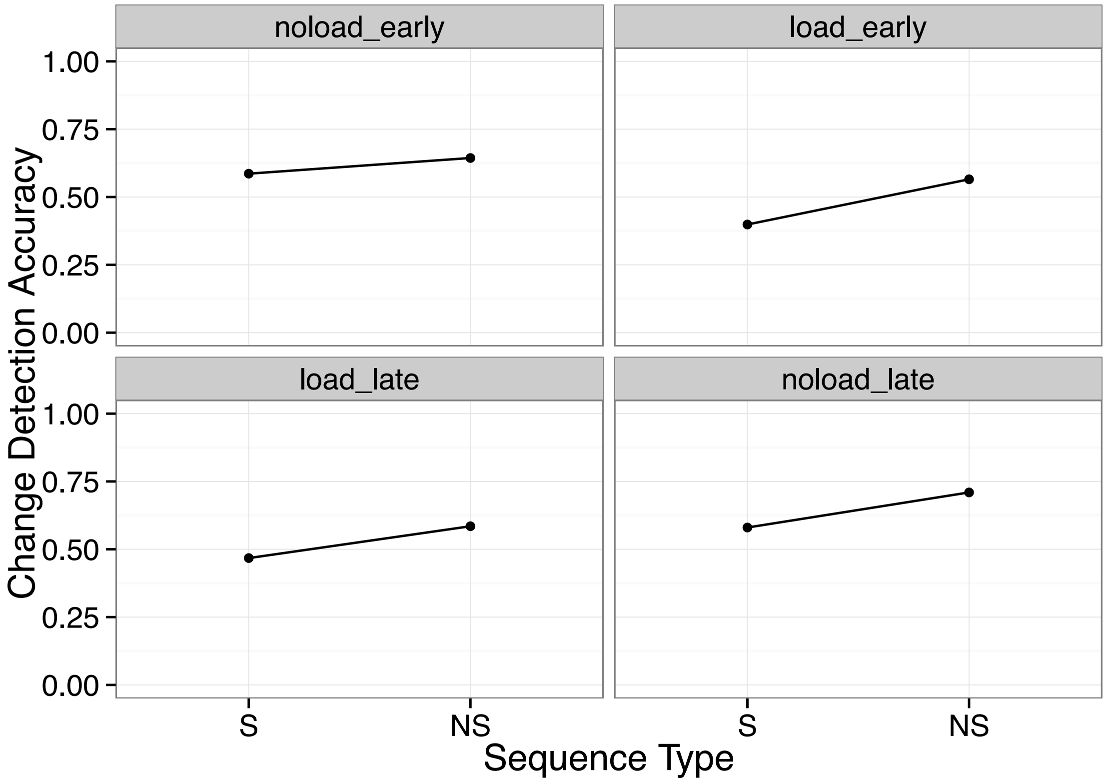

Figure 9 Three way Sequence type x task load x taskCond interaction.

Although the four-way interaction was significant, taskCond itself was not a parameter of interest. In addition, the inclusion of taskCond as a fixed effect introduced a large number of nuisance parameters not of theoretical interest, but necessary to explore higher-level interaction, (i.e. two-way interactions between taskCond and WM, CF and seqtype). In order to reduce the parameter space and make more explicit comparisons, I created a new variable, taskComb, by combining the levels of task, load and no load, with the levels of task order, early and late, generating a factor with four levels rather than two, two-level factors (See Table 6.2), and re ran the analysis in Model 3. In addition, I used posterior means and standard deviations from Study 1 Model 3 (Table 3.6) for CF, WM, sequence type main effects and for the CF by sequence type interaction and the CF x WM interaction.

Model 3

Inspection of the WAIC between Models 2 and 3 suggest that parameterization of task and presentation order as a single factor improved overall model fit. In addition, the significant effects of taskComb suggest that task load decreased accuracy by 24% when presented early compared to non-loaded trials early and 15% when task load was presented late. In addition, Model 3 yielded a significant taskcomb x WM interaction suggesting that the effect of WM was significantly stronger in non-loaded trials presented late. Furthermore, a significant taskComb by CF interaction suggested that the effect of CF significantly reduced only when task load was presented early. Significant seqtype by taskComb interactions suggested the effect of sequence type was significantly higher in all other conditions. Finally, the significant CF x seqtype x task load interaction present in Model 2 was only marginally significant in Model 3.

Table 16 Regression Model 3 output for trials 11 – 64, Study 2.
Task load and taskCond collapsed. Priors used for CF, WM, seqtype, CFxseqtype and CFxWM are posteriors in Table 5 Regression Model 2 output for trials 11 - 64, Study 1.. Significant predictors in bold.

M and SD represent the average and standard deviation of posterior sample estimates for each parameter. LL and UL represent the upper and lower bounds of the 95% HDI. *b* is unstandardized effect of each parameter in percent. Model run in STAN with four 6,000-step chains and a 1,000 step burn in period. $\hat{R} < 1.1$ indicates good convergence. Neff reflects effective sample size.

Parameter	M	SD	LL	UL	*b*	% in ROPE	Neff	Rhat
Fixed Effects								
(Intercept)	0.12	0.11	-0.09	0.32	0.02		4277	1
cf	**0.27**	**0.08**	**0.1**	**0.43**	**0.05**	**0.004**	**6290**	**1**
wm	0.1	0.08	-0.04	0.25	0.02	0.212	6100	1
seqtypeNS	0.2	0.09	0.02	0.38	0.04	0.050	9816	1
taskcombload_early	**-0.95**	**0.15**	**-1.24**	**-0.65**	**-0.19**	**0.000**	**4559**	**1**
taskcombload_late	**-0.59**	**0.12**	**-0.83**	**-0.35**	**-0.12**	**0.000**	**9394**	**1**
taskcombnoload_late	-0.07	0.15	-0.36	0.23	-0.01	0.234	4472	1
ltacc	**0.21**	**0.06**	**0.09**	**0.34**	**0.04**	**0.005**	**6165**	**1**
cf_X_wm	0.05	0.07	-0.1	0.19	0.01	0.420	6511	1
cf_X_seqtypeNS	0.05	0.09	-0.13	0.23	0.01	0.360	10208	1
wm_X_taskcombload_early	0.15	0.12	-0.09	0.39	0.03	0.159	5595	1
wm_X_taskcombload_late	0.11	0.09	-0.07	0.29	0.02	0.217	12574	1
wm_X_taskcombnoload_late	0.23	0.12	0	0.47	0.05	0.056	5363	1
cf_X_taskcombload_early	**-0.34**	**0.13**	**-0.61**	**-0.08**	**-0.07**	**0.013**	**5770**	**1**
cf_X_taskcombload_late	0.04	0.12	-0.19	0.28	0.01	0.300	9831	1
cf_X_taskcombnoload_late	**-0.48**	**0.14**	**-0.75**	**-0.22**	**-0.09**	**0.001**	**6209**	**1**
seqtypeNS_X_taskcombload_early	**0.56**	**0.16**	**0.26**	**0.87**	**0.11**	**0.000**	**11532**	**1**
seqtypeNS_X_taskcombload_late	0.36	0.16	0.05	0.67	0.07	0.300	10699	1
seqtypeNS_X_taskcombnoload_late	**0.39**	**0.16**	**0.09**	**0.7**	**0.08**	**0.012**	**10518**	**1**
cf_X_wm_X_taskcombload_early	0.13	0.12	-0.1	0.36	0.03	0.175	5300	1
cf_X_wm_X_taskcombload_late	0.01	0.09	-0.17	0.19	0.00	0.416	13442	1
cf_X_wm_X_taskcombnoload_late	-0.07	0.12	-0.3	0.16	-0.01	0.271	5624	1
cf_X_seqtypeNS_X_taskcombload_early	0.15	0.15	-0.14	0.44	0.03	0.165	12341	1
cf_X_seqtypeNS_X_taskcombload_late	**-0.3**	**0.16**	**-0.6**	**0.01**	**-0.06**	**0.045**	**11287**	**1**
cf_X_seqtypeNS_X_taskcombnoload_late	0.19	0.15	-0.1	0.48	0.04	0.125	11859	1
sigma	0.68	0.03	0.63	0.73	0.13		11731	1
Random Effects	Var	SE						
Subject	0.5	0.05					6805	1
WAIC 1093								

Table 18 presents the results of Model 3 with uninformative priors. In general, the results between both Models are in close correspondence, however, Model 3 with uninformative priors failed to identify a significant main effect of CF and CF by task load and WM by task load interactions. This is likely due to much higher posterior sample correlations present without informative priors. Despite these differences the WAIC for Model 3 with informative priors was slightly smaller suggesting incorporating prior information from Study 1 provided a better fit to the data.

Table 17 Regression Model 3 output for trials 11 – 64, no priors, Study 2.
Task load and taskCond collapsed. Uninformative priors used. Significant predictors in bold. M and SD represent the average and standard deviation of posterior sample estimates for each parameter. LL and UL

represent the upper and lower bounds of the 95% HDI. *b* is unstandardized effect of each parameter in percent. Model run in STAN with four 6,000-step chains and a 1,000 step burn in period. $\hat{R}$ < 1.1 indicates good convergence. Neff reflects effective sample size.

Parameter	M	SD	LL	UL	*b*	% in ROPE	Neff	Rhat
Fixed Effects								
(Intercept)	0.12	0.12	-0.11	0.35	0.02		8352	1
cf	0.24	0.12	0	0.48	0.05	0.050	9095	1
wm	0.19	0.1	-0.01	0.38	0.04	0.075	9449	1
seqtypeNS	**0.27**	**0.12**	**0.03**	**0.51**	**0.05**	**0.030**	**12066**	**1**
taskcombload_early	**-0.96**	**0.16**	**-1.27**	**-0.64**	**-0.19**	**0.000**	**10872**	**1**
taskcombload_late	**-0.57**	**0.13**	**-0.83**	**-0.32**	**-0.11**	**0.000**	**16214**	**1**
taskcombnoload_late	-0.07	0.16	-0.38	0.24	-0.01	0.226	10100	1
ltacc	**0.22**	**0.06**	**0.09**	**0.35**	**0.04**	**0.004**	**13731**	**1**
cf_X_wm	-0.04	0.1	-0.24	0.16	-0.01	0.346	10252	1
cf_X_seqtypeNS	-0.03	0.13	-0.29	0.22	-0.01	0.295	12229	1
wm_X_taskcombload_early	0.07	0.14	-0.2	0.33	0.01	0.256	9997	1
wm_X_taskcombload_late	0.07	0.1	-0.12	0.26	0.01	0.309	20000	1
wm_X_taskcombnoload_late	0.15	0.14	-0.11	0.42	0.03	0.161	9579	1
cf_X_taskcombload_early	-0.32	0.16	-0.64	0.01	-0.06	0.035	10003	1
cf_X_taskcombload_late	0.04	0.14	-0.23	0.31	0.01	0.272	15332	1
cf_X_taskcombnoload_late	-0.46	0.16	-0.78	-0.14	-0.09	0.005	9615	1
seqtypeNS_X_taskcombload_early	**0.49**	**0.18**	**0.15**	**0.84**	**0.10**	**0.005**	**15580**	**1**
seqtypeNS_X_taskcombload_late	**0.29**	**0.17**	**-0.06**	**0.63**	**0.06**	**0.005**	**15474**	**1**
seqtypeNS_X_taskcombnoload_late	0.32	0.17	-0.02	0.66	0.06	0.045	15827	1
cf_X_wm_X_taskcombload_early	0.22	0.14	-0.04	0.49	0.04	0.081	10080	1
cf_X_wm_X_taskcombload_late	0.05	0.1	-0.14	0.24	0.01	0.352	20000	1
cf_X_wm_X_taskcombnoload_late	0.02	0.14	-0.25	0.28	0.00	0.288	10270	1
cf_X_seqtypeNS_X_taskcombload_early	0.23	0.18	-0.12	0.58	0.05	0.101	15635	1
cf_X_seqtypeNS_X_taskcombload_late	-0.22	0.18	-0.58	0.15	-0.04	0.105	15041	1
cf_X_seqtypeNS_X_taskcombnoload_late	0.27	0.18	-0.08	0.61	0.05	0.075	14453	1
sigma	0.68	0.03	0.63	0.73	0.13		20000	1
Random Effects	Var	SE						
Subject	0.5	0.05					13215	1
WAIC 1097								

Because results from Model 3 with informative priors suggested a marginally significant interaction between WM and taskComb as well as marginal three-way interactions between sequence type, CF, and taskComb for non-loaded trials presented late, I re-ran the analysis in Model 3 with noload_late as the reference level. However, because of differential transfer effects observed in Study 1, I was unable to provide informative priors for Model 4.

Model 4

Results from Model 4 present an entirely different landscape of effects than Models 1 – 3. Most significantly Model 4 yielded a marginally significant *negative* effect of CF, suggesting that for no load trials presented late, a one-unit increase in CF resulted in a 4% decrease in accuracy. In addition, Model 4 identified a significant positive effect of WM of similar magnitude to the effect of CF in Models 1 – 3 such that participants' accuracy increased by 7% for every one-unit increase in WM. However, the significant sequence type by CF interaction indicates that, as suggested by Figure 8, the effect of CF remains positive for non-switch trials.

Table 18 Regression Model 4 output for trials 11 – 64, Study 2
Task load and taskCond collapsed. Uninformative priors used. Significant predictors in bold. M and SD represent the average and standard deviation of posterior sample estimates for each parameter. LL and UL represent the upper and lower bounds of the 95% HDI. b is unstandardized effect of each parameter in percent. Model run in STAN with four 6,000-step chains and a 1,000 step burn in period. $\hat{R}$ < 1.1 indicates good convergence. Neff reflects effective sample size.

Parameter	M	SD	LL	UL	*b*	% in ROPE	Neff	Rhat
Fixed Effects								
(Intercept)	0.05	0.11	-0.16	0.27	0.01		6252	1
cf	-0.22	0.11	-0.42	0	-0.04	0.053	7366	1
wm	**0.34**	**0.1**	**0.15**	**0.53**	**0.07**	**0.001**	**7084**	**1**
seqtypeNS	**0.59**	**0.12**	**0.35**	**0.84**	**0.12**	**0.000**	**8677**	**1**
taskcombload_early	**-0.89**	**0.13**	**-1.13**	**-0.64**	**-0.17**	**0.000**	**10621**	**1**
taskcombnoload_early	0.07	0.16	-0.25	0.38	0.01	0.222	7550	1
taskcombload_late	**-0.5**	**0.16**	**-0.82**	**-0.19**	**-0.10**	**0.001**	**7648**	**1**
ltacc	**0.22**	**0.06**	**0.1**	**0.35**	**0.04**	**0.004**	**9449**	**1**
cf_X_wm	-0.02	0.09	-0.2	0.16	0.00	0.408	7916	1
cf_X_seqtypeNS	**0.24**	**0.12**	**0**	**0.47**	**0.05**	**0.048**	**9898**	**1**
wm_X_taskcombload_early	-0.08	0.09	-0.26	0.1	-0.02	0.286	18000	1
wm_X_taskcombnoload_early	-0.15	0.14	-0.42	0.12	-0.03	0.162	6558	1
wm_X_taskcombload_late	-0.08	0.14	-0.35	0.19	-0.02	0.244	7038	1
cf_X_taskcombload_early	0.14	0.12	-0.09	0.38	0.03	0.169	11013	1
cf_X_taskcombnoload_early	**0.46**	**0.16**	**0.14**	**0.78**	**0.09**	**0.005**	**7631**	**1**
cf_X_taskcombload_late	**0.49**	**0.16**	**0.18**	**0.81**	**0.10**	**0.003**	**7390**	**1**
seqtypeNS_X_taskcombload_early	0.17	0.18	-0.17	0.52	0.03	0.139	10546	1
seqtypeNS_X_taskcombnoload_early	**-0.32**	**0.17**	**-0.66**	**0.02**	**-0.06**	**0.044**	**11099**	**1**
seqtypeNS_X_taskcombload_late	-0.03	0.18	-0.38	0.31	-0.01	0.215	11257	1
cf_X_wm_X_taskcombload_early	**0.2**	**0.09**	**0.02**	**0.38**	**0.04**	**0.043**	**18000**	**1**
cf_X_wm_X_taskcombnoload_early	-0.02	0.14	-0.28	0.25	0.00	0.285	7334	1
cf_X_wm_X_taskcombload_late	0.03	0.14	-0.23	0.3	0.01	0.279	6918	1
cf_X_seqtypeNS_X_taskcombload_early	-0.04	0.17	-0.37	0.29	-0.01	0.234	11207	1
cf_X_seqtypeNS_X_taskcombnoload_early	-0.27	0.18	-0.61	0.07	-0.05	0.078	11718	1
cf_X_seqtypeNS_X_taskcombload_late	**-0.48**	**0.18**	**-0.83**	**-0.14**	**-0.09**	**0.006**	**12571**	**1**
sigma	0.68	0.03	0.63	0.73	0.13		18000	1
Random Effects	Var	SE						
Subject	0.5	0.05					13215	1
WAIC 1097								

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Study 2 Results Summary

H1: If CF provides local benefits to change detection, then I should observe a positive predictive relationship between CF and accuracy in the first ten trials.

Results from analysis of trials 1 – 10 failed to provide support for H1.

H2: In accordance with Study 1 CF should exhibit a positive predictive relationship with change detection.

Models 2 and 3 identified a significant main effect of CF providing support for H2. However, Models 1 and 4 failed to find a significant effect of CF failing to provide evidence for H2.

H3: If task load reduces individuals' attention control resulting in increased processing of distractions, then trials without load should have higher accuracy than trials under load.

Models 1 – 4 identified a significant main effect of task load such that participants performed significantly worse on trials under load than those without; providing support for H3.

H4: If perseveration on previous change types exists, then trial sequences where the current change type matches the most recently correctly identified change type (non-

switch sequences) should have higher accuracy than trial sequences where the current change type differs from the previously identified change type (switch sequences).

Models 1 – 4 failed to provide support for H4.

H5: If the effect of perseveration of change types exists, then it should be modulated by the presence or absence of task load. Specifically, task load should increase differences between switch sequence types and non-switch sequence types.

Models 1 and 2 identified a significant sequence type by task load interaction such that the effect of sequence type was stronger under task load; providing support for H5.

H6: If the effect of perseveration of change types exists, then it should be modulated by an individual's level of CF. Specifically, individuals higher in CF should be better able to overcome perseveration and thus CF should reduce or eliminate differences between trials where the current change type is the same or different than the previously correctly identified change.

Models 1 – 4 failed to provide support for H6.

H7: If CF modulates perseveration effects due to oscillation between different change types, and the presence of task load increases the differences between sequence types, then the magnitude of the CF by sequence type interaction should be greater under task load.

Model 2 identified a significant task load by taskCond by sequence type by CF interaction, providing partial support for H7. Specifically, when load was presented late, the CF by sequence type interaction followed the form predicted by H7. However, when load was presented early and in the subsequent trials with no load, the interaction remained significant but in the opposite direction, providing support against H7.

H8: If CF reflects an individual's ability to shift the scope of attention and task load reduces the control of attention, then the magnitude of the relationship between CF and change detection should be greater under task load.

Models 1 and 2 failed to provide support for H8. However, Model 2 revealed that the effect of CF was contingent on when task load was presented. Specifically, the magnitude of the effect of CF for early trials with no load was significant and similar to Study 1. This effect was slightly stronger when task load was presented late, but this difference was not significant; failing to provide support for H8. However, when task load was presented early the effect of CF was eliminated and reversed direction in subsequent trials with no load; providing evidence against H8.

H9: If WM reflects and individual's ability to control their attention and task load reduces the control of attention, then the magnitude of the relationship between CF and change detection should be greater under task load.

Models 1 and 4 identified a significant main effect of WM providing evidence for H9. However, Models 2 – 3 did not identify a significant effect of WM failing to provide evidence for H9.

H10: If WM is only predictive of change blindness when the scope of attention can adaptively shift, then CF should modulate the effect of WM. Specifically, the magnitude of the effect of WM should increase as CF increases.

Models 1 – 4 failed to provide support for H10.

H11: If the magnitude of the effect of WM is greater under task load and CF modulates the effect of WM, then the magnitude of the CF by WM interaction should be greater under task load.

Model 4 identified a significant WM by CF by task load interaction providing support for H11. Specifically, the magnitude of the CF by WM interaction was larger and in the expected direction when task load was presented early. However, Models 1 – 3 failed to provide support for H11.

Task load and Sequence Type effects

In general, all Study 2 models suggested a large effect of task load such that regardless of presentation order observers were significantly more likely to detect a change when not under load. However, the effect of task load was strongest when load was presented early in the task. This effect is driven by the fact the early loaded tasks had the lowest average accuracy and the non-loaded trials following had the highest average accuracy.

In addition, in contrast to Study 1, I observed a much larger significant main effect of sequence type in Study 2 models. These effects interacted with both CF and task load suggesting that: 1) task load increased perseverative effects of switch trials, and 2) CF provided a protection against this effect when load was presented late. Furthermore, when task load was presented early the CF by sequence type interaction reversed its form, suggesting that higher CF increased the perseverative effects of sequence type.

CF and WM

Results from Study 2 replicated Study 1 effects for non-loaded trials presented early and subsequent trials with secondary task load presented late. However, the effect of CF was significantly reduced, and in the case of no-load trials presented late, almost reversed. Unlike Study 1, Study 2 yielded significant main effects of WM predicting change detection. Model 3 indicated that WM yielded a significant positive predictive relationship for task load presented early and subsequent non-loaded trials presented late.

CHAPTER 7: DISCUSSION STUDY 2

Based on the results of Study 2 I have evidence to suggest that CF is not a universal predictor of change blindness performance. While models that evaluated the effect of CF in conditions similar to those in Study 1 identified a significant positive predictive relationship between CF and change blindness, the effect of CF was essentially eliminated for early trials under load and reversed during the subsequent non-loaded trials, especially for switch trials. The dramatic differences in the effect of CF and its interaction with sequence type between presentation orders, once again suggests differential transfer was at play in Study 2.

In addition, Study 2 revealed a significant positive predictive relationship between WM and change blindness. These results suggest that WM and CF both play a significant role in explaining the incidence of change blindness. However, the nature of the conditions in which CF or WM play a significant role is complex. In particular, differential transfer effects in Study 2 suggest that early exposure to secondary task load yields a significant effect of WM not present when task load is presented late in the task. Furthermore, this effect of WM (and null/negative effect of CF) persists in subsequent no-load trials in a manner that is not present in no-load trials presented early. Thus, Study 2 does not conclusively identify that WM is only predictive of change detection under load. However, results suggest that WM appears a significant predictor when task load is presented early and that early presentation of task load alters the performance on subsequent no load trials.

CHAPTER 8: GENERAL DISCUSSION

The phenomenon of change blindness is of material interest to basic and applied psychologists alike as it serves as a fertile testing ground for theories of attention and highlights one of the critical limitations in of the human visual attention system. Despite the ubiquity of the effect, the existence of individual differences in rates of change blindness suggests that observer features may explain partially why this phenomenon occurs. In this dissertation, I set out to explore two cognitive individual differences in attention control, WM and CF, not often studied in conjunction with each other, and even less so in the context of change blindness. In general, this dissertation was successful inasmuch as I identified conditions in which both CF and WM predict change blindness as well as situations where the two constructs interact. Furthermore, the pattern of results from Study 1 and 2 as well as the lack of strong zero-order correlations suggest that WM and CF are indeed dissociable constructs and represent independent aspects of attention control.

Individual differences in attention control predict change blindness

Coherence Theory

The role of attention in change blindness is well documented (Rensink, 1997). Specifically as Rensink et al. (1997) and Rensink (2000) demonstrated focused attention is required for the successful detection of changes. In order to better understand how individual differences attention control may manifest themselves in a change blindness task it is helpful to couch our results in the context of coherence theory (Rensink, 2008). In general, coherence theory states that early vision is composed of volatile, low-level “proto-objects” which are quickly revised and overwritten whenever new information is present. Focused attention functions as a metaphorical hand which grabs a limited number of proto objects and endows them a much higher degree of coherence. After focused attention is withdrawn proto-objects return to the “primordial ooze” of dynamic incoherent proto-objects (Figure 8.1). Importantly, coherence theory dictates that only one “nexus” of proto-objects can be attended at one time, but that the illusion of consistency and availability of visual information is maintained similar to a computer terminal accessing a network. In essence the information appears available because whenever information about a specific area is called it appears. Similarly, it would be a mistake to conclude that a single laptop per se has the entirety of the internet locally stored, instead a computer terminal, much like attention gives the user access to a vast network of information.

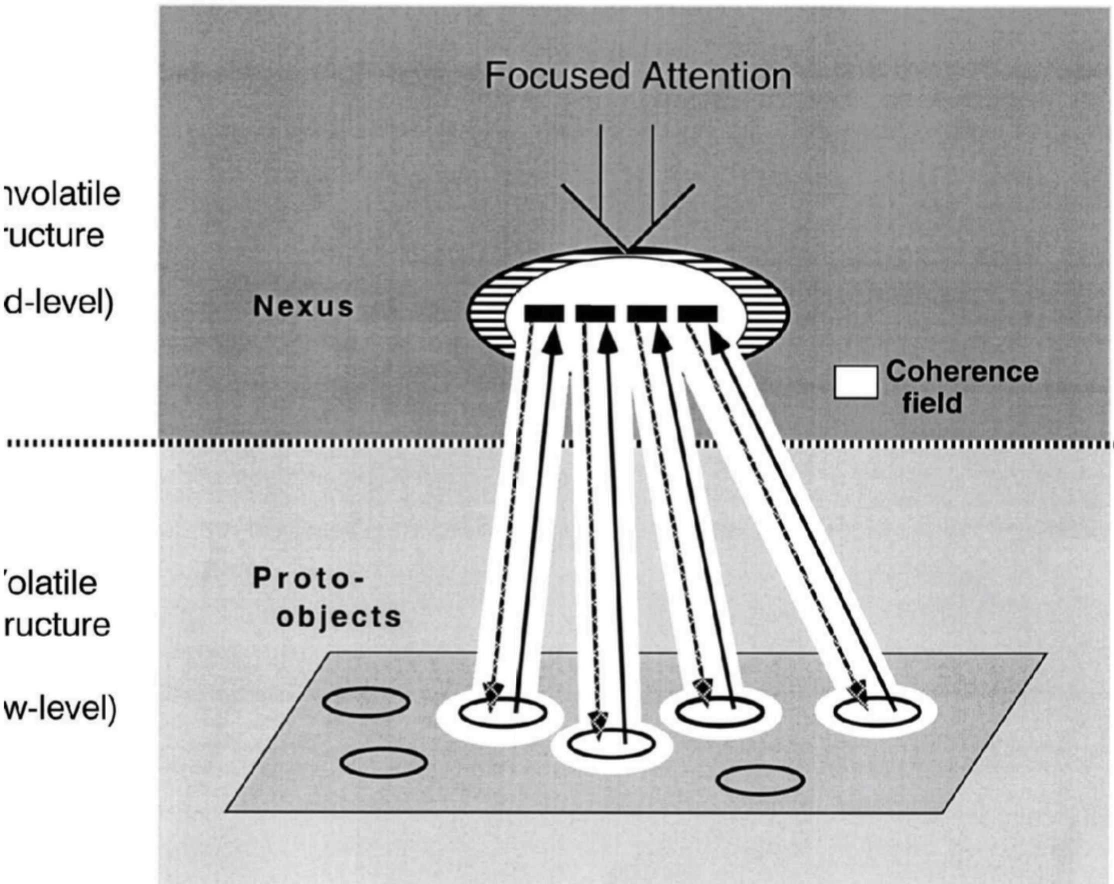

Figure 10 Schematic of coherence field.
Reproduced from Rensink (2000).

In addition, Renisnk (2000) goes on to define a triadic architecture of dynamic scene perception that explains how attention may be guided and explore a visual scene over time. As Figure 10 illustrates, System I constitutes low-level vision which produces volatile proto-objects, these proto objects then go on to inform the “gist” and layout the non-attentional (i.e. not conscious per se) tuning mechanisms in System III. System III in turn guides and guides the distribution of attention throughout a scene and prioritizes certain objects over others.

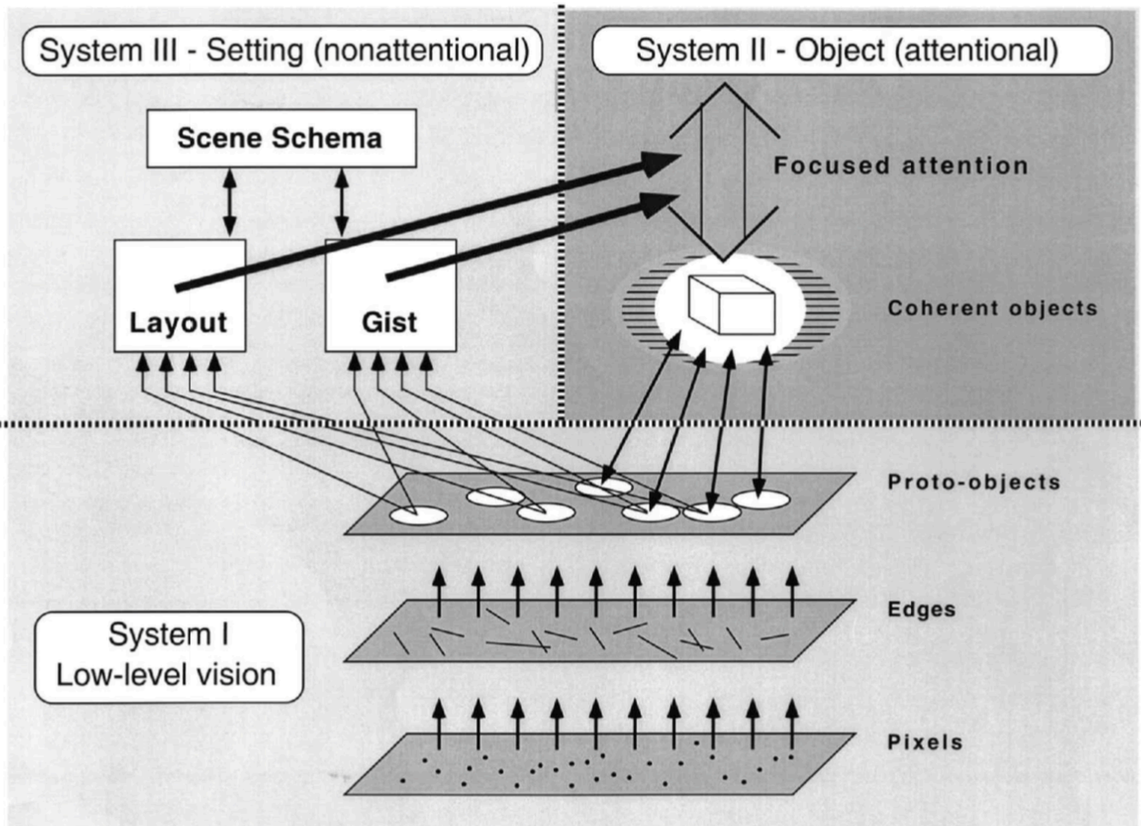

Figure 11Triadic architecture.
Reproduced from Rensink, 2000

WM and coherence theory

Turning our attention back to individual differences in attention control how/where might WM and CF influence this triadic structure? The influence of WM appears at first obvious. Specifically, WM as measured by the Ospan and Rspan task reflects the number of proto objects that can be collected in a nexus within a single focused attention grasp. However, Rensink (2000) argues that the memory system at play here, visual short-term memory (vSTM; Luck & Vogel, 1997), is much more basic and volatile than the higher-level memory structure measured by complex span tasks. Furthermore, although Rensink (2000b) has shown that observers find changes faster in arrays with smaller numbers of objects, suggesting that attentional capacity improves search, I failed to find a significant predictive relationship between WM and change blindness in almost every condition except for under load and subsequent non-load in Study 2. Thus rather than WM representing a pure measure of the capacity of proto objects that can be sampled at a given time, perhaps higher WM aids maintenance of a coherent nexus over time. Under conditions without load, or when observers have had sufficient exposure to the task, maintenance of coherence is simple enough that attention control plays little role in successful detection. However, when task load is presented early, this throttles the ability of focused attention either by forcing continuous temporal shifts between the secondary load task and visual search or by weakening the "grip" on proto-objects within a single nexus. When this is the case, attention control of the form provided by WM may become much more relevant and aid in the successful coherence maintenance of nexus across time long enough to identify the change object.

It is important to note that this conclusion differs sharply from predictions laid out in Chapter 1 as well as from results observed by Smilek et al. (2006) and Watson (2010). However, in both cases, researchers used small array size static visual displays. Thus it may be that the 'relaxed' cognitive strategy they identified as successful only benefits observer detection when set size is relatively small and consistent. The inclusion of complex dynamic representations in the change blindness task used here likely swamped any potential benefits "waiting for the target to come to you" may have provided. Put in terms of coherence theory, what Smilek et al. (2006) and Watson (2010) may have been observing would be akin to a looser, wider grip of attention, which incorporated more proto objects and, coupled with temporal stability, yielded more efficient search performance.

Similarly, Pringle et al. (2001) and Jensen (2011) have observed positive zero-order correlations between attentional breadth and change blindness. In particular, they found that individuals with a wider FFOV are able to find changes more quickly. In terms of coherence theory this too may be viewed as a wider, looser grip of attention. However, results from Study 2 suggest that increasing memory load demand failed to produce a wider attentional breadth in any appreciably positive sense. Instead our results were much more in line with Lavie's cognitive load theory (Lavie et al., 2000), which states that when selective attention is an active process the scope of selective attention is narrowed to block out irrelevant features. However, when additional cognitive load is presented the inhibitory component of selective attention begins to break down, thus providing irrelevant information and distractors the opportunity to capture attention. Initially, this may seem like a positive effect in an ill-defined task like change blindness whereby it is unclear what is a 'relevant' versus irrelevant section of the visual scene until after detection has occurred. Put another way, conceptually, the intrusion of "distractors" in a change blindness task could improve performance as it incorporates a higher number of objects into awareness. However results from Study 2 suggest once again, that this is not the case. Furthermore, in a similar study, Lee et al. (2007) found that in a dynamic change blindness task, taking place in a driving simulator, participants were more likely to miss key changes to the driving environment when presented with a secondary auditory task. Thus, it seems that in Study 2, when subjects were placed under load early, the strength of the grip of attention of proto-objects sampled from the array was weakened allowing potentially for the incorporation of a higher number of proto-objects. Similar to widening the focus of a lens, more of the environment is captured but at the cost of resolution. However, with a reduction in attentional focus comes a reduction in the temporal coherence of the nexus of proto-objects resulting in overall poorer detection.

CF and coherence theory

The role of CF in coherence theory is less clear than WM. Clearly, the results of both studies suggest that local effects of CF exist and thus must manifest themselves somewhere in the coherence theory framework. One possibility is that CF manifests itself within System III rather than System II at all. Specifically, CF may be responsible for adapting and updating the context in which focused attention is operating. Coherence theory in general, seems to suggest that System III only influences attention via scene schemas or other top-down knowledge structures related to real world perception. Given that this study used only basic shapes, it is unlikely that the 'gist' of the arrays likely provided much meaningful context. However, the effect of CF may suggest that System III is also responsible for broadly tuning the attentional capture system in the vein of Folk et al. (1994). Furthermore, the effect of cueing in Study 1 also supports the notion that System III can prioritize the focus of attention with basic information in context-free arrays. Taken together, CF may manifest itself as flexible prioritization structure that dynamically shifts the focus of attention to different stimulus features. Finally, the effects of sequence type observed in Study 2 suggest that without CF this prioritization can get 'stuck' and make it more difficult to find changes that that differ from the last successfully detected especially under load.

Alternatively, CF could manifest itself in the nexus of information. As Scott (1962) originally put forth, higher CF in individuals is indicative of the ease by which the view of an existing cognitive structure is shifted in response to new environmental stimuli. Thus if the nexus of proto-objects itself is viewed as a cognitive structure, CF may manifest as the number of dimensions that are compared between successive samples either in sequence or in parallel. If this is the case CF may be viewed as originating from System III or potentially at a higher level than that described by coherence theory. Future work examining the relationship between CF, change blindness and eye movements may further elucidate the role of CF in change blindness and how it contributes to coherence theory.

Limitations and Future Work

One major limitation of this dissertation was the evidence of differential transfer in both Study 1 and 2. Although the presence of differential transfer did not render the results of my analyses uninterpretable, the additional temporal component made interpretation of the results much more difficult. In future studies, a between-subjects design might be more desirable as it appears that receiving cueing or task load early has a distinct effect on subsequent trials. In addition, this study had participants completing over 60 trials of different changes. However, in most change blindness studies the number of trials is typically 20 trials or less (Resink et al. 2000; Simons & Levin, 1998 for example). The higher number of trials was in part due to the inclusion of both cued and uncued and trials with and without task load for each participant in Study 1 and 2 respectively. The higher number of trials could have led to fatigue, which was reported by some participants. The additional decay of attention control over time (i.e. vigilance; Davies & Parasuraman, 1982) was an unforeseen and uncontrolled factor.

Change blindness stimuli used in this dissertation were intentionally devoid of context. However, given the rich literature on the phenomenon of change blindness as it occurs in real world scenes, future work could examine these relationships with additional scene content. In particular it would be interesting to see how sequence type effects might manifest themselves between shifts of change type and object type. For example, switch trials might not just represent a switch from the changing stimulus dimension (e.g. color to size), but could also represent categorical shifts (e.g. people to inanimate objects or buildings to vehicles). In addition, it is possible that the effect of CF may be even more pronounced when there is considerable complexity and objects or dimensions to prioritize. Finally, this study only examined one level of cognitive load, present or absent, but future work could examine how lower levels of cognitive load, e.g. simply shadowing the number stream or responding if there is a specific number, or higher levels of cognitive load, e.g. responding if the current number matches the number two or even back instead of one back, alter performance.

Conclusion

In conclusion, this work demonstrates that individual differences in attention control predict change blindness. The mechanisms of precisely how CF and WM interact within the framework of coherence theory are still not fully understood. However, results from the studies presented here lay a foundation for future work in this area. Ultimately, the phenomenon of change blindness reveals the fundamental instability between the physiological mechanisms of vision and cognitive architecture of perception. A deeper understanding of its causes elucidates more of the opaque nature of consciousness as well as provides practical guidance for designers developing systems for human interaction.

REFERENCES

Akaike, H. (1973), "Information theory and an extension of the maximum likelihood principle", in Petrov, B.N.; Csáki, F., 2nd International Symposium on Information Theory, Tsahkadsor, Armenia, USSR, September 2-8, 1971, Budapest: Akadémiai Kiadó, p. 267-281.

Angelone, B., & Severino, S. (2008). Effects of individual differences on the ability to detect changes in natural scenes. *Journal of Vision*, *8*(6), 461-461.

Asano, M., Kanaya, S., & Yokosawa, K. (2008). Proofreaders show a generalized ability to allocate attention to detect changes. *Journal of Vision*,*8*(6), 462-462.

Bayes, & Price, M. (1763). An essay towards solving a problem in the doctrine of chances. by the late rev. mr. bayes, frs communicated by mr. price, in a letter to john canton, amfrs. *Philosophical Transactions (1683-1775)*, 370-418.

Beck, M. R., Levin, D. T., & Angelone, B. (2007). Change blindness blindness: Beliefs about the roles of intention and scene complexity in change detection. *Consciousness and Cognition*, *16*(1), 31 51.

Beck, M. R., Angelone, B. L., & Levin, D. T. (2004). Knowledge about the probability of change affects change detection performance. *Journal of Experimental Psychology: Human Perception and Performance*, *30*(4), 778.

Box, G., & Jones, S. (1992). Split-plot designs for robust product experimentation. *Journal of Applied Statistics*, *19*(1), 3-26.

Colflesh, G. J., & Conway, A. R. (2007). Individual differences in working memory capacity and divided attention in dichotic listening. *Psychonomic Bulletin & Review*, *14*(4), 699-703.

Colflesh, G. J., & Wiley, J. (2013). Drunk, but not blind: The effects of alcohol intoxication on change blindness. *Consciousness and cognition*, *22*(1), 231-236.

Conway, A. R., Cowan, N., & Bunting, M. F. (2001). The cocktail party phenomenon revisited: The importance of working memory capacity.*Psychonomic Bulletin & Review*, *8*(2), 331-335.

Conway, A. R., Kane, M. J., & Engle, R. W. (2003). Working memory capacity and its relation to general intelligence. *Trends in cognitive sciences*, *7*(12), 547-552.

Cowan, N. (2001). The magical number 4 in short-term memory: A reconsideration of mental storage capacity. Behavioral and Brain Sciences, 24, 87–185.

Daneman, M., & Carpenter, P. A. (1980). Individual differences in working memory and reading. *Journal of verbal learning and verbal behavior*, *19*(4), 450-466.

Davies DR, Parasuraman R (1982): The Psychology of Vigilance. London: Academic Press.

de Fockert, J. W., Rees, G., Frith, C. D., & Lavie, N. (2001). The role of working memory in visual selective attention. *Science*, *291*(5509), 1803-1806.

Edwards, W., Lindman, H., & Savage, L. J. (1963). Bayesian statistical inference for psychological research. *Psychological Review*, *70*(3), 193.

Fitousi, D., & Wenger, M. J. (2011). Processing capacity under perceptual and cognitive load: A closer look at load theory. *Journal of experimental psychology: human perception and performance*, *37*(3), 781.

Fisher, R. A. (1925). *Statistical Methods for Research Workers.* Edinburgh: Oliver and Boyd.

Folk, C. L., Remington, R. W. and Wright, J. H. (1994). The structure of attentional control: Contingent attentional capture by apparent motion, abrupt onset, and color. *Journal of Experimental Psychology: Human Perception and Performance, 20*, 317-329.

Folk, C. L., Remington, R. W., & Johnston, J. C. (1992). Involuntary covert orienting is contingent on attentional control settings. *Journal of Experimental Psychology: Human Perception and Performance, 18,* 1030-1044.

Gelman, A., & Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical science*, 457-472.

Gravetter, F., & Wallnau, L. (2006). *Statistics for the behavioral sciences*. Cengage Learning.

Grimes, J. (1996). On the failure to detect changes in scenes across saccades. In K. Akins (Ed.), (*Vancouver studies in cognitive science: Vol. 2: Perception*, (pp. 89–110). New York: Oxford University Press.

Gonzalez, C. A., Figueroa, I. J., Bellows, B. G., Rhodes, D., & Youmans, R. J. (2013). A new behavioral measure of cognitive flexibility. In *Engineering Psychology and Cognitive Ergonomics. Understanding Human Cognition* (pp. 297-306). Springer Berlin Heidelberg.

Hastings, W.K. (1970). "Monte Carlo Sampling Methods Using Markov Chains and Their Applications". *Biometrika* 57 (1): 97–109.

He, J., & McCarley, J. S. (2010). Executive working memory load does not compromise perceptual processing during visual search: Evidence from additive factors analysis. *Attention, Perception, & Psychophysics*, *72*(2), 308-316.

Heitz, R. P., Unsworth, N., & Engle, R. W. (2005). Working memory capacity, attention control, and fluid intelligence. *Handbook of understanding and measuring intelligence*, 61-77.

Henderson, J. M. (2003). Human gaze control during real-world scene perception. *Trends in cognitive sciences*, *7*(11), 498-504.

Henderson, J. M., & Hollingworth, A. (1999). The role of fixation position in detecting scene changes across saccades. *Psychological Science*, *10*(5), 438-443.

Hoffman, M. D., & Gelman, A. (2014). The no-U-turn sampler: Adaptively setting path lengths in Hamiltonian Monte Carlo. *The Journal of Machine Learning Research*, *15*(1), 1593-1623.

Ionescu, T. (2012). Exploring the nature of cognitive flexibility. *New ideas in psychology*, *30*(2), 190-200.

Jensen, M. (2011). *Predicting noticing: individual differences in change blindness and inattentional blindness* (Masters Thesis). Available at IDEALS.illinois.edu.

Jolliffe, I. (2002). *Principal component analysis*. John Wiley & Sons, Ltd.

Kane, M. J., Bleckley, M. K., Conway, A. R., & Engle, R. W. (2001). A controlled-attention view of working-memory capacity. *Journal of Experimental Psychology: General*, *130*(2), 169.

Kane, M. J., & Engle, R. W. (2000). Working-memory capacity, proactive interference, and divided attention: limits on long-term memory retrieval. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *26*(2), 336.

Kruschke, J. (2010a). *Doing Bayesian data analysis: A tutorial introduction with R*. Academic Press.

Kruschke, J. K. (2011). Bayesian assessment of null values via parameter estimation and model comparison. *Perspectives on Psychological Science*,*6*(3), 299-312.

Kruschke, J. K. (2010b). What to believe: Bayesian methods for data analysis.*Trends in cognitive sciences*, *14*(7), 293-300.

Kruschke, J. K. (2013). Bayesian estimation supersedes the t test. *Journal of Experimental Psychology: General*, *142*(2), 573.

Lavie, N., Hirst, A., de Fockert, J. W., & Viding, E. (2004). Load theory of selective attention and cognitive control. *Journal of Experimental Psychology: General*, *133*(3), 339.

Lavie, N., & Tsal, Y. (1994). Perceptual load as a major determinant of the locus of selection in visual attention. *Perception & Psychophysics*, *56*(2), 183-197.

Lavie, N. (2006). The role of perceptual load in visual awareness. *Brain research*, *1080*(1), 91-100.
Lee, Y. C., Lee, J. D., & Boyle, L. N. (2007). Visual attention in driving: The effects of cognitive load and visual disruption. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *49*(4), 721-733.

Luck, S.J., & Vogel, E.K. (1997). The capacity of visual working memory for features and conjunctions. Nature, 390, 279–281.

Masuda, T., & Nisbett, R. E. (2006). Culture and change blindness. *Cognitive Science*, *30*(2), 381-399.

Metropolis, N., Rosenbluth, A. W., Rosenbluth, M. N., Teller, A. H., & Teller, E. (1953). Equation of state calculations by fast computing machines. *The journal of chemical physics*, *21*(6), 1087-1092.

Mueller, S. T. & Piper, B. J. (2014). The Psychology Experiment Building Language (PEBL) and PEBL Test Battery. *Journal of Neuroscience Methods, 222*, 250-259.

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The unity and diversity of executive functions and their contributions to complex "frontal lobe" tasks: A latent variable analysis. *Cognitive psychology*, *41*(1), 49-100.

Neal, R. (2011). Handbook of Markov Chain Monte Carlo, chapter 5: MCMC Using Hamiltonian Dynamics.

O'Regan, J. K., Rensink, R. A., & Clark, J. J. (1999). Change-blindness as a result of 'mudsplashes'. *Nature*, *398*(6722), 34-34.

O'Regan, J.K. (1992). Solving the "real" mysteries of visual perception: The world as an outside memory.*Canadian Journal of Psychology/Revue Canadienne de Psychologie, 46*(3)

Peterson, M. S., & Wong, J. H. (2008). Were you paying attention to where you looked? The role of executive working memory in visual search. *Psychonomic Bulletin & Review*, *15*(2), 372-377.

Pringle H.L., Irwin D.E., Kramer A.F., & Atchley P. (2001). The role of attentional breadth in perceptual change detection. *Psychonomics Bulletin & Review*, 8(1), 89-95.

Rensink, R. A., O'Regan, J. K., & Clark, J. J. (1997). To see or not to see: The need for attention to perceive changes in scenes. *Psychological Science*, *8*(5), 368-373.

Rensink, R. A. (2008). On the applications of change blindness. *Psychologia*,*51*(2), 100-106.

Rensink, R. A. (2000). The dynamic representation of scenes. *Visual cognition*,*7*(1-3), 17-42.

Rensink, R. A. (2000b). Visual search for change: A probe into the nature of attentional processing. *Visual cognition*, *7*(1-3), 345-376.

Scott, W. A. (1962). Cognitive complexity and cognitive flexibility. *Sociometry*, 405-414.

Simons, D. J., Chabris, C. F., Schnur, T., & Levin, D. T. (2002). Evidence for preserved representations in change blindness. *Consciousness and Cognition*,*11*(1), 78-97.

Simons, D. J., & Levin, D. T. (1998). Failure to detect changes to people during a real-world interaction. *Psychonomic Bulletin & Review*, *5*(4), 644-649.

Smilek, D., Enns, J. T., Eastwood, J. D., & Merikle, P. M. (2006). Relax! Cognitive strategy influences visual search. *Visual Cognition*, *14*(4-8), 543-564.

Stan Development Team. 2014. *Stan Modeling Language Users Guide and Reference Manual, Version 2.5.0.*

Stan Development Team. 2014. RStan: the R interface to Stan, Version 2.5. http://mc-stan.org/rstan.html.

Unsworth, N., Heitz, R. P., Schrock, J. C., & Engle, R. W. (2005). An automated version of the operation span task. *Behavior research methods*, *37*(3), 498-505.

Vehtari, A., & Gelman, A. (2014). WAIC and cross-validation in Stan. Unpublished manuscript retrieved from http://www.stat.columbia.edu/~gelman/research/unpublished/waic_stan.pdf

Wagenmakers, E. J., Lodewyckx, T., Kuriyal, H., & Grasman, R. (2010). Bayesian hypothesis testing for psychologists: A tutorial on the Savage–Dickey method. *Cognitive psychology*, *60*(3), 158-189.

Watson, M. R., Brennan, A. A., Kingstone, A., & Enns, J. T. (2010). Looking versus seeing: Strategies alter eye movements during visual search. Psychonomic Bulletin & Review, 17, 543–549.

Watanabe, S. (2010). Asymptotic equivalence of Bayes cross validation and widely applicable information criterion in singular learning theory. *Journal of Machine Learning Research 11,* 3571–3594.

Youmans, R. J., Figueroa, I. J., & Kramarova, O. (2011, September). Reactive task-set switching ability, not working memory capacity, predicts change blindness sensitivity. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 55, No. 1, pp. 914-918). Sage Publications.

Youmans, R., & Ohlsson, S. (2008). Suboptimal adaptations to redundant instrument failure: The role of noticing behavior in feedback effectiveness.*Ergonomics*, *41*, 441-475.

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