Online Appendices

Appendix A. Experimental Design for Detail for Experiment 1—fMRI

Figure A1. The completion of the permission warning training, showing all acceptable and malicious permissions. Subjects were required to accurately identify all risky permissions before proceeding with the fMRI experiment.

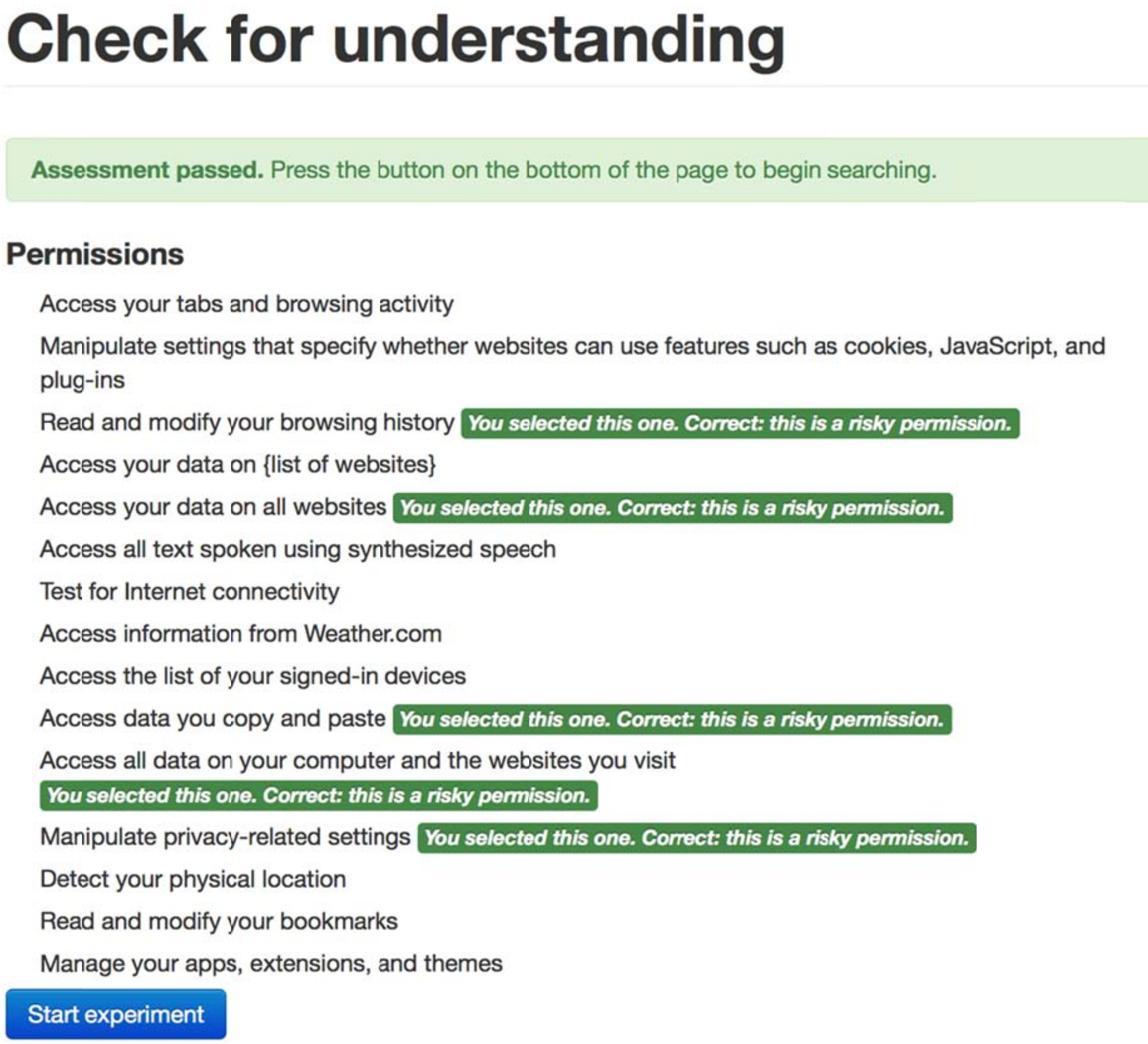


Figure A2. **The encode screen. Displayed for 5 seconds.**

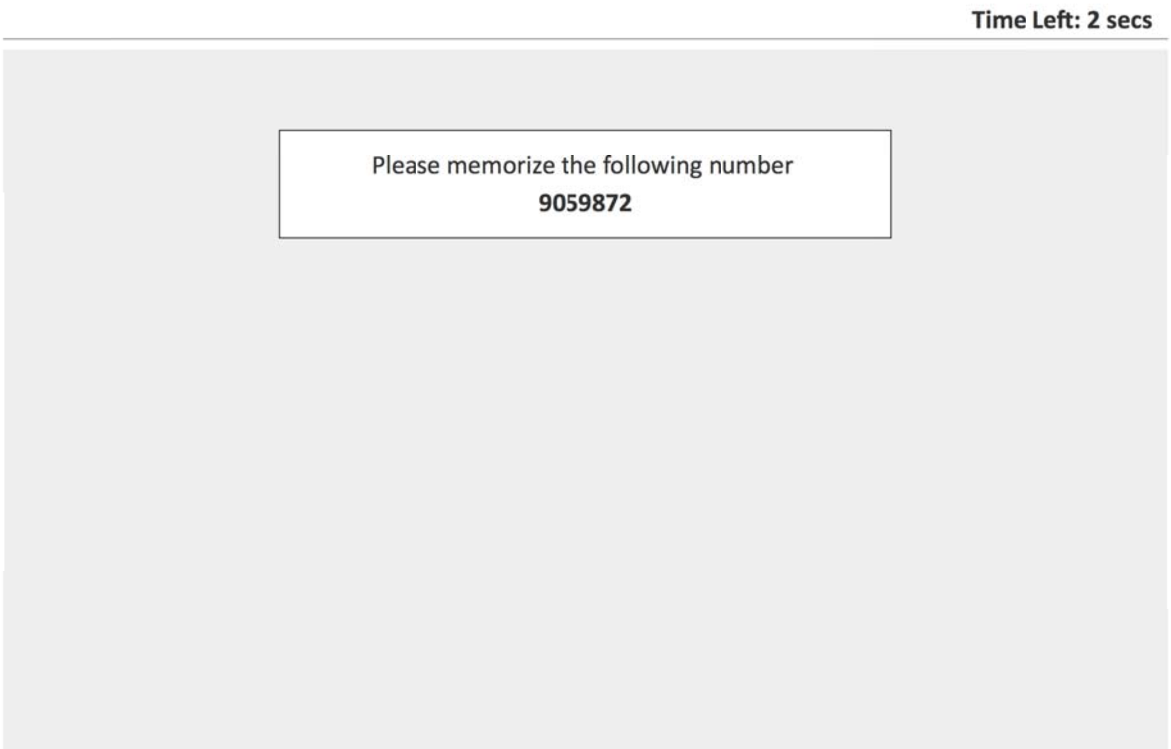


Figure A3. **The rehearsal screen. Displayed for 7 +|- 3 seconds.**

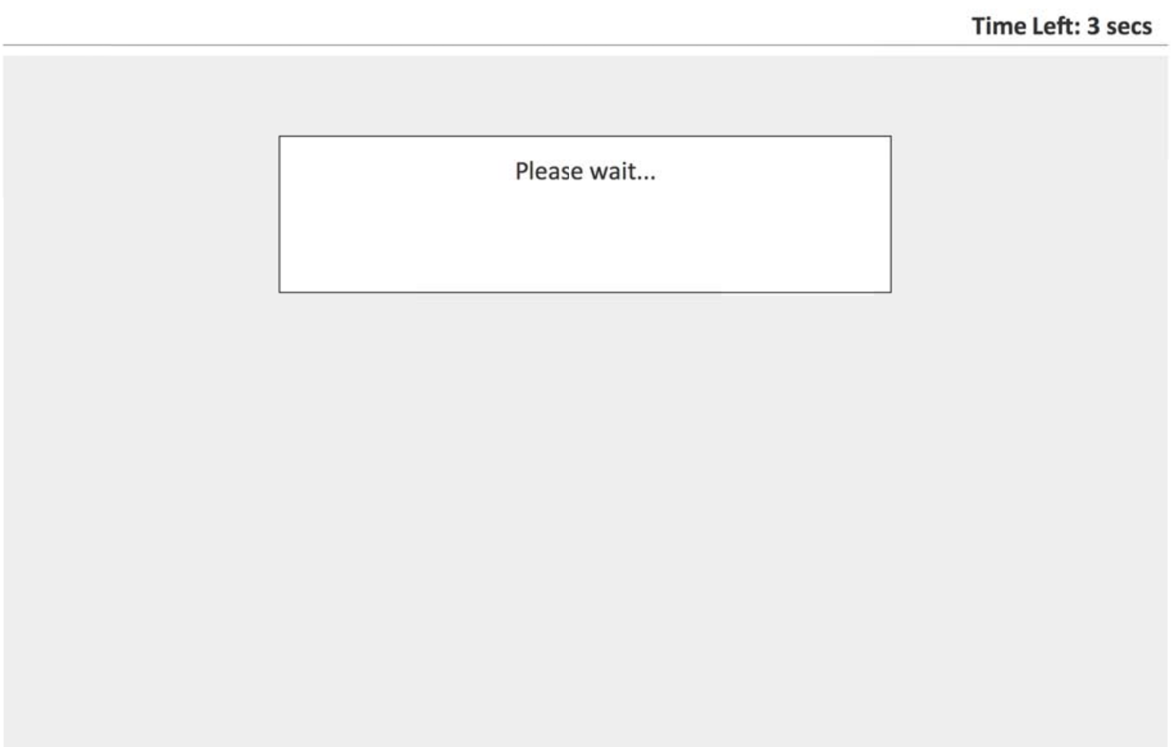


Figure A4. The retrieval screen. Displayed for 7 +|- 3 seconds.

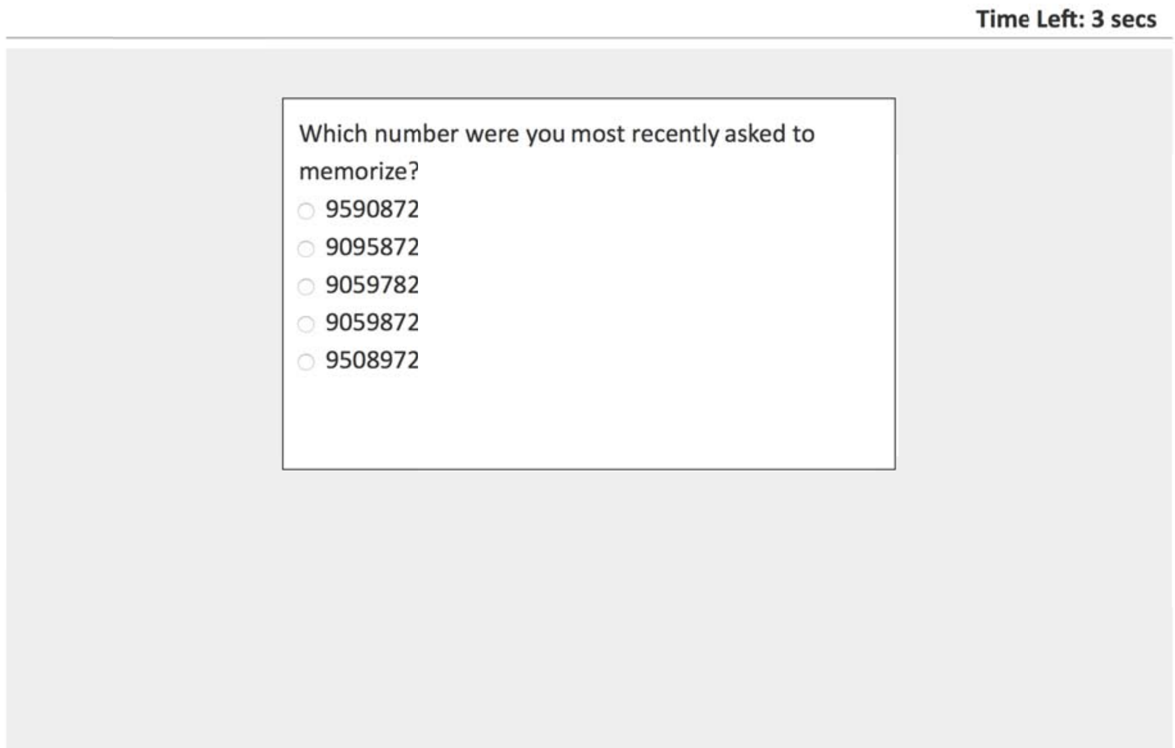
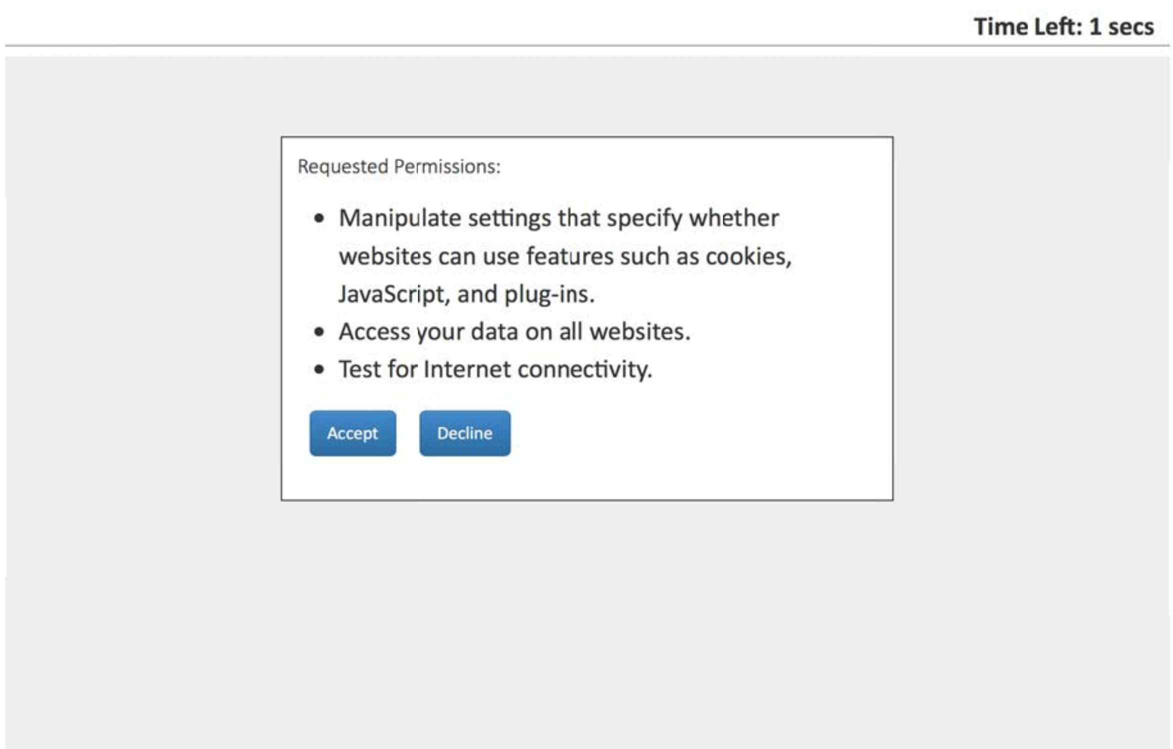


Figure A5. The permission-warning screen. Displayed for 7 +|- 3 seconds.



Appendix B. fMRI Results Tables

Table B1. Significant Clusters of Activation in the Warning-Only > High-DTI Contrast

	#Voxels	Peak x	Peak y	Peak z
R Middle Temporal Gyrus	1150	-44	68	24
L Cuneus	294	2	77	18
R Medial Temporal Lobe	119	-32	20	-15
R Parahippocampal Gyrus	111	-2	47	6
L Medial Temporal Lobe	87	38	2	-21
R Uncus	63	-14	-2	-24
L Cerebellum	56	23	83	-39
L Middle Temporal Gyrus	49	59	17	-9
L Inferior Occipital Gyrus	46	44	83	-6
R Inferior Occipital Gyrus	42	-38	77	-3

Table B2. Significant Clusters of Activation in the Low-DTI > High-DTI Contrast

	#Voxels	Peak x	Peak y	Peak z
R Medial Temporal Lobe	261	-26	2	-27
R Middle Temporal Gyrus	82	-50	68	18
L Middle Frontal Gyrus	49	14	-44	24
L Medial Temporal Lobe	47	38	2	-27

Appendix C. Pilot Tests for Experiments 1 and 2

Experiment 1: Pilot Test

Prior to administering our experiment in the fMRI scanner, we conducted a pilot test using Amazon's Mechanical Turk to see if the treatments resulted in a behavioral difference concerning security message disregard. In this pilot test, we followed the same procedure as to be used in the fMRI data collection, except that participants only completed four repetitions in each treatment.

Thirty-three Mechanical Turk Masters—an elite class of workers vetted for their consistency and high accuracy in the Mechanical Turk marketplace (Amazon Mechanical Turk 2015)—participated in the pilot test. Following the recommendations of Steelman et al. (2014), we used a US-based demographic to mirror our student-based population of native-English speakers. The average age of participants was 32.2 years.

In the analysis, we specified a Mixed Effects Logistic Regression model to account for the repeated measure nature of the data to test our manipulations. We included disregard as the binary dependent variable (1 for disregard, 0 for not). We then included the participant ID and the condition order (e.g., which condition the participants saw 1st, 2nd, etc.) as random effects. We also included the conditions (as dummy variables) as fixed effects. The warning-only condition was specified as the reference or baseline group. Finally, we included the trial repetition number as a fixed effect (e.g., the *n*th warning within a given condition) to explore whether participants' behavior changed across trials as a result of habituation. Wald statistics were calculated for significance tests.

We found support for our manipulations of DTI. The high-DTI condition had significantly higher disregard compared to the warning-only condition, $z = 3.667$, $p < .001$, $\beta = 1.213$. When treating the low-DTI condition as the reference group, the high-DTI condition also had significantly higher disregard than the low-DTI condition, $z = 2.539$, $p < .05$, $\beta = 0.782$. However, the low-DTI condition did not statistically differ from the Warning-Only condition, $z = 1.243$, $p > .05$, $\beta = 0.431$. Furthermore, the trial repetition number did not significantly influence adherence, indicating that habituation did not influence the results,

z = -0.018, p > .05, β = -0.002. The r-squared of the model was 0.176. The overall disregard percentages for each condition are shown in Table C1.

Table C1. Pilot Test Warning Performance

	Security Warning	
Treatment	**Disregard**	**Regard**
High-DTI	36.92%	63.08%
Low-DTI	23.39%	76.61%
Warning-Only	17.74%	82.26%

Experiment 2: Pilot Test

We pilot tested the experimental procedure with 236 participants on Amazon's Mechanical Turk (MTurk). In a post-task survey, we collected manipulation check items to confirm that our low-DTI conditions had higher DTI than our high-DTI conditions. In addition, we collected feedback on the experiment through a free-response question. This provided insight into why people accepted or rejected the message, which informed the conceptualization of our dependent variable.

Appendix D. fMRI Technical Details

Equipment

MRI scanning took place at a university MRI research facility with the use of a Siemens 3T Tim Trio scanner. For each scanned participant, we collected a high-resolution structural MRI scan for functional localization in addition to a series of functional scans to track brain activity during the performance of the various tasks. Structural images were acquired with a T1-weighted magnetization-prepared rapid acquisition, including a gradient-echo (MP-RAGE) sequence with the following parameters: TE = 2.26 ms, flip angle = 9°, slices = 176, slice thickness = 1.0 mm, matrix size = 256 × 215, and voxel size = 1 mm × 0.98 mm × 0.98 mm. Functional scans were acquired with a gradient-echo, echo-planar, T2*-weighted pulse sequence with the following parameters: TR = 2000 ms, TE = 28 ms, flip angle = 90°, slices = 40, slice thickness = 3.0 mm (no skip), matrix size = 64 × 64, and voxel size = 3.44 mm × 3.44 mm × 3 mm.

Protocol

Participants were given a verbal briefing about the MRI procedures and the task, and were then situated supine in the scanner. Visual stimuli were viewed using a mirror attached to the head coil reflecting a large monitor outside the scanner that was configured to display images in reverse so that they appeared normal when viewed through the mirror. We first performed a 10-second localizer scan, followed by the 7-minute T1 structural scan. Following these, we started the experimental task. Total time in the scanner was about 50 minutes.

Analysis

The MRI data were analyzed with the Analysis of Functional Images (AFNI) software suite (Cox 1996). Pre-processing steps were as follows: functional data were slice-time corrected to account for differences in acquisition time for different slices of each volume. Then, each volume was realigned by registering it with the middle volume of each run to account for low-frequency motion. Data from each run were aligned to the run nearest in time to the acquisition of the structural scan. The structural scan was then co-registered to the functional scans. Spatial normalization was accomplished by first warping the structural scan to the Talairach Atlas (Talairach and Tournoux 1988), followed by warping to a template brain with Advanced Neuroimaging Tools (ANTs; Advants 2011).

Single subject analyses were carried out using the GLM approach. Regressors for each event type were entered into the design matrix: memory code display, high-DTI warning, low-DTI rehearsal, memory retrieval, low-DTI warning, Warning-Only warning, and Working-memory Only rehearsal. Regressors coding for motion (three translations and three rotations) were also entered into the design matrix. Periods without explicit task demands were included in the model as an implicit baseline (the breaks shown in Figure 5). Stimulus durations were modeled as illustrated in Figure 5 and as described in Section 3.2 — Methodology. Statistical parameter maps (beta values) from the single-subject regression analysis were smoothed using a 5-mm FWHM Gaussian kernel. Beta values for the conditions of interest were then entered into group-level analyses (whole-brain voxel-wise *t*-tests), which were used to determine significant clusters of activation or functional regions of interest (ROIs). We controlled for multiple comparisons by using Monte Carlo simulations to determine the voxels-wise p-value (p<.02) and spatial extent threshold (k>40 contiguous voxels or 1080mm^3) that resulted in a family-wise error rate p<.05.

As the order of presentation was randomized, we paired the MRI data with the behavioral data and interaction with the web-based program using a signal generated by the scanner at the beginning of each task.

Appendix E. Comparing Low-DTI and Warning-Only Conditions in Experiment 1—fMRI

We replicate the hypotheses 1–3 of Experiment 1, this time comparing MTL activation and security message disregard between low-DTI and Warning-Only scenarios. Similar to earlier hypotheses, we anticipate that presenting the warning after the primary task will lead to lower activity in the MTL region of the brain than when users' only task is to process security warnings. The bottleneck model of DTI predicts that this decrease in MTL is caused by a switching cost that is not present when people only have a single task—i.e., people's responses are usually more error prone and slower immediately following a task switch (Monsell 2003; Rogers and Monsell 1995). In summary, we hypothesize:

$H1_{AppendixE}$. For the MTL region of the brain, activity will be lower under the low-DTI condition compared to the Warning-Only condition.

Likewise, we predict that this task switching cost in low-DTI scenarios will increase security message disregard. With the cost of task switching, users activate the MTL less to respond to the security warning. Likewise, optimal MTL activation and other brain functions may be initially unavailable during the task switch. As a result, as previously discussed, performance will decrease as people are less able to draw on information in declarative memory to respond to the security message. In summary,

$H2_{AppendixE}$. Security message disregard will be higher under the low-DTI condition as compared to the Warning-Only condition.

Finally, if low-DTI decreases activity in the MTL compared to the Warning-Only task ($H1_{AppendixE}$) and this decrease explains why security message disregard will be higher in low DTI versus the Warning-Only task ($H2_{AppendixE}$), we hypothesize that the difference in MTL activation between low DTI and Warning-Only tasks should predict the change in security message disregard between the two conditions. In summary,

$H3_{AppendixE}$. Between the Warning-Only and low-DTI conditions, a decrease in activation of the MTL will predict an increase in security warning disregard.

Low-DTI versus Warning-Only Treatment fMRI Analysis

We now analyze Hypotheses $H1–3_{AppendixE}$ that explore the relationship between brain activation and security message disregard in the low-DTI and Warning-Only treatments. In this analysis, we examined the neural correlates of responding to security warnings under dual-task conditions by comparing activation for the low-DTI warning rehearsal period (in which participants were required to maintain a seven-digit code in their working memory and respond to the warning stimulus) with activation for the warning in the Warning-Only condition using paired *t*-tests. We exclusively masked the results of this comparison with the warning versus baseline comparison to eliminate spurious activations (such as visual responses to the stimulus and motor responses from manipulating the trackball). We did not find any significant clusters (ROIs) of activation. We specifically examined the activation in the MTL, and whether it was higher in the Warning-Only condition than in the low-DTI condition. However, we did not find any significant results ($t(23) = 1.171$, $p = .254$). These findings show that the differences between the MTL activation in low-DTI and Warning-Only treatments are minimal, and suggest that timing of the warning messages to occur after distinct tasks (rather than in the middle) can be cognitively similar to addressing warning messages alone. Thus, $H1_{AppendixE}$ was not supported.

We examined how the difference in DTI between the low-DTI and Warning-Only conditions influenced participants' actual security message disregard. A chi-squared test indicated that there was no difference in security message disregard in the low-DTI treatment and the Warning-Only treatment ($\chi2(1) = 0.560$, $p > .05$). $H2_{AppendixE}$ was therefore not supported.

Finally, we explored whether the difference in MTL activation between the high-DTI and low-DTI treatments predicted participants' change regarding security message disregard. We specified a regression model with participants' change in security message disregard as the dependent variable and participants' change in MTL between the two treatments as the independent variable. Consistent with

$H1_{AppendixE}$ and $H2_{AppendixE}$, the analysis did not produce significant results: $\beta = -.067$, $t(23) = .315$, $p > .05$, $H3_{AppendixE}$ was not supported. These results are summarized in Table E1.

Summary of Results of Supplemental Hypotheses for Experiment 1

In summary, we found that there was no statistical difference between the Warning-Only treatment and the low-DTI treatment ($H1–3_{AppendixE}$), indicating that the switching cost within task switching was less than we expected. This finding suggests that the timing security messages to appear at low-DTI times could improve security message disregard to levels similar to when the security message is the primary task.

Table E1. Summary of Supplemental Hypotheses and Analyses for Experiment 1

#	Hypothesis	Analysis	Result
Comparing Low-DTI to Warning-Only			
$H1_{AppendixE}$	For the MTL region of the brain, activity will be lower under the low-DTI condition compared to the Warning-Only condition.	fMRI	Not Supported
$H2_{AppendixE}$	Security message disregard will be higher under the low-DTI condition as compared to the Warning-Only condition.	Behavioral	Not Supported
$H3_{AppendixE}$	Between the Warning-Only and low-DTI conditions, a decrease in activation of the MTL will predict an increase in security warning disregard.	fMRI–Behavioral	Not Supported

Appendix F. Experimental Design for Detail for Experiment 2—Chrome High-DTI Treatments

Figure F1. High-DTI: During a video.

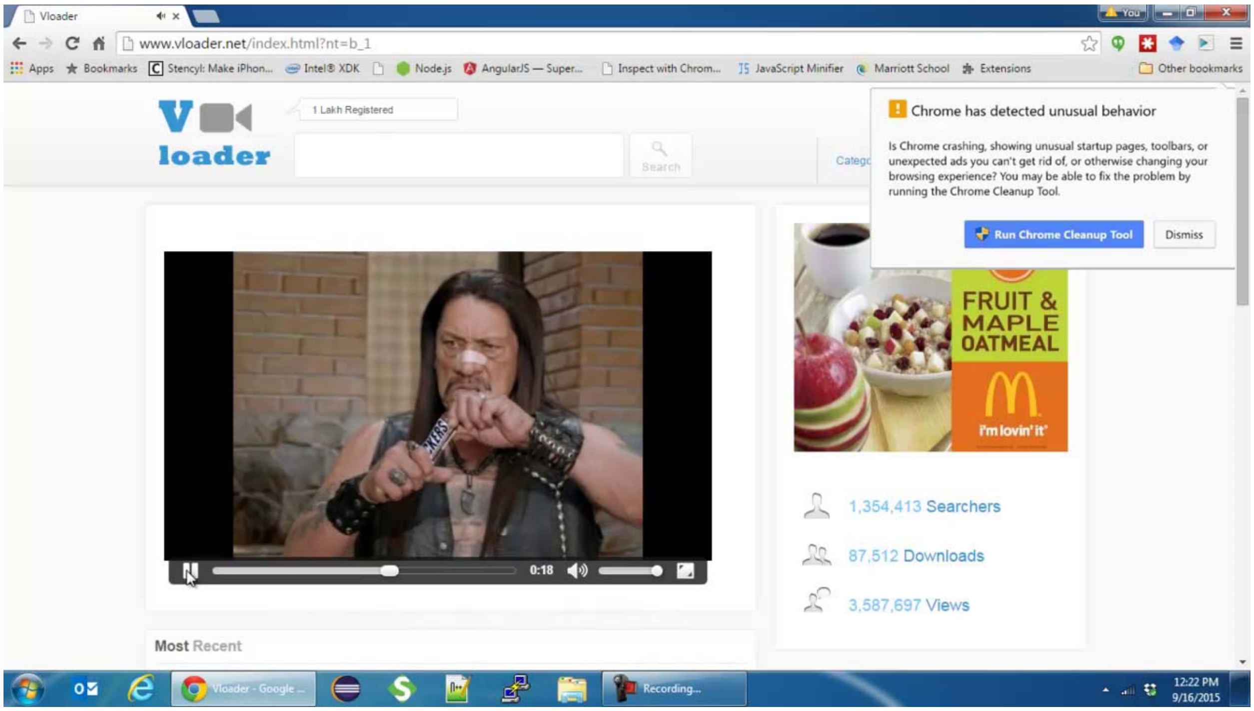


Figure F2. High-DTI: While typing.

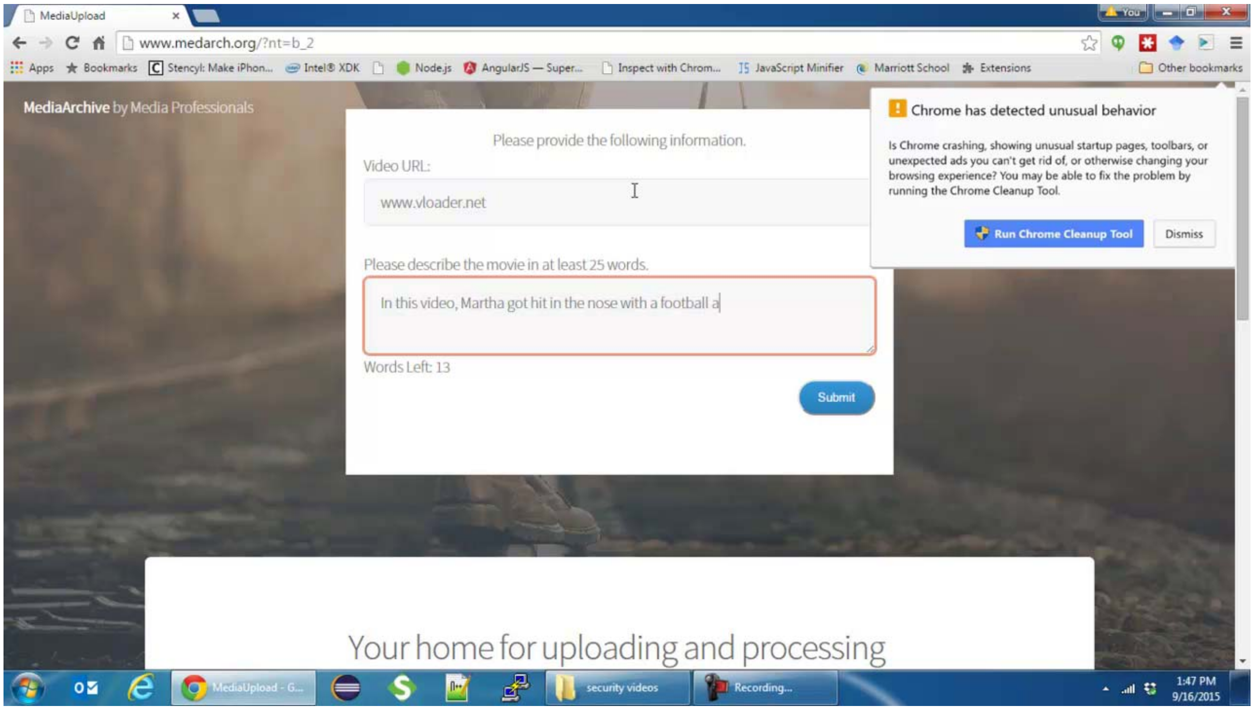


Figure F3. High-DTI: While transferring information.

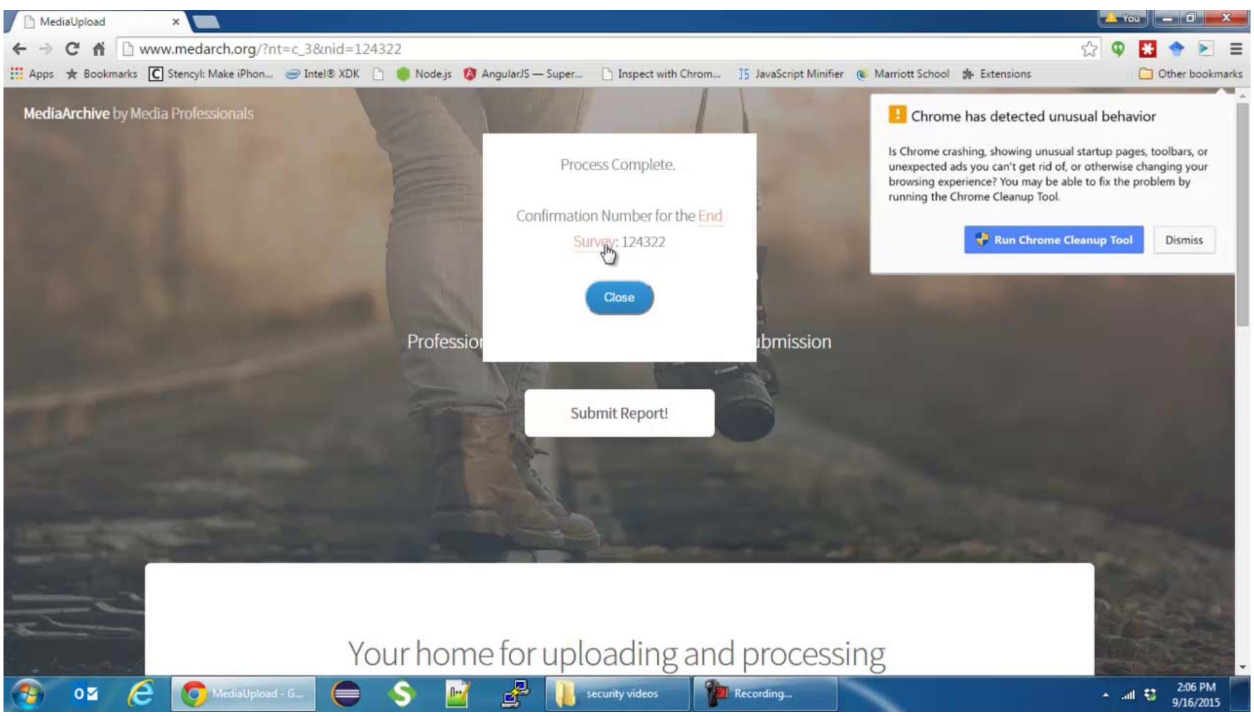
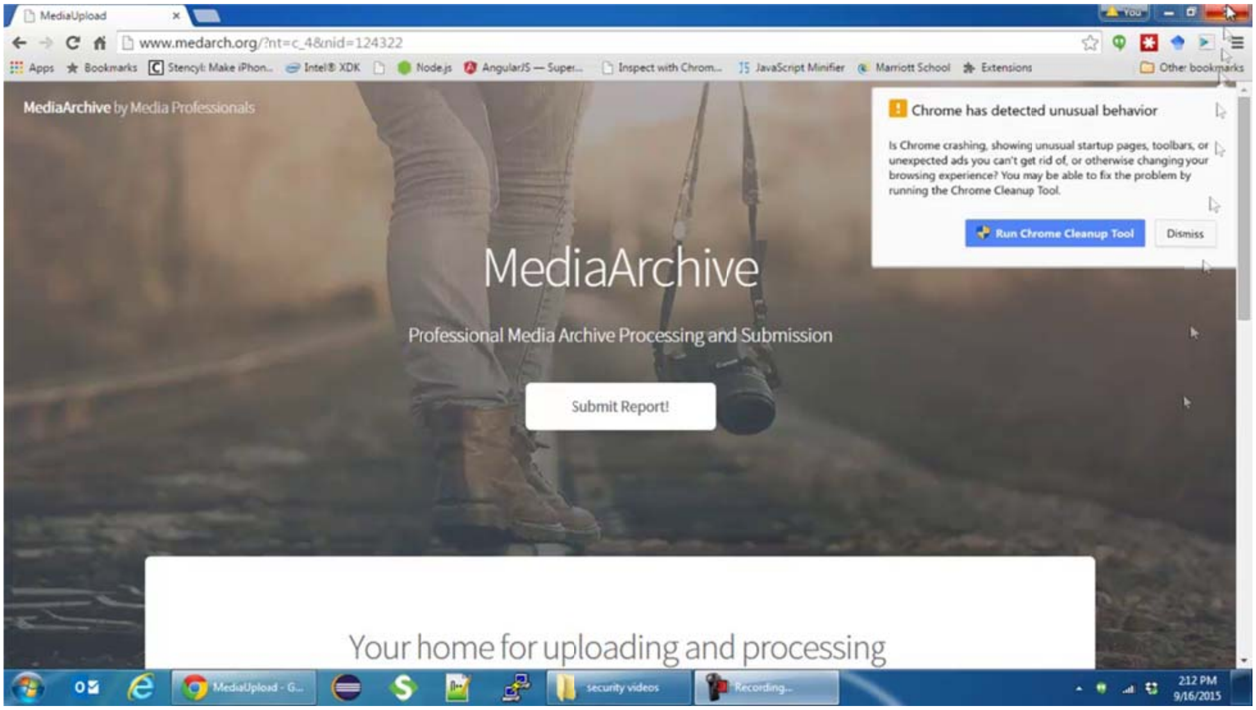


Figure F4. High-DTI: On the way to close the window.



Low-DTI Treatments

Figure F5. LowDTI-1: On first page load.

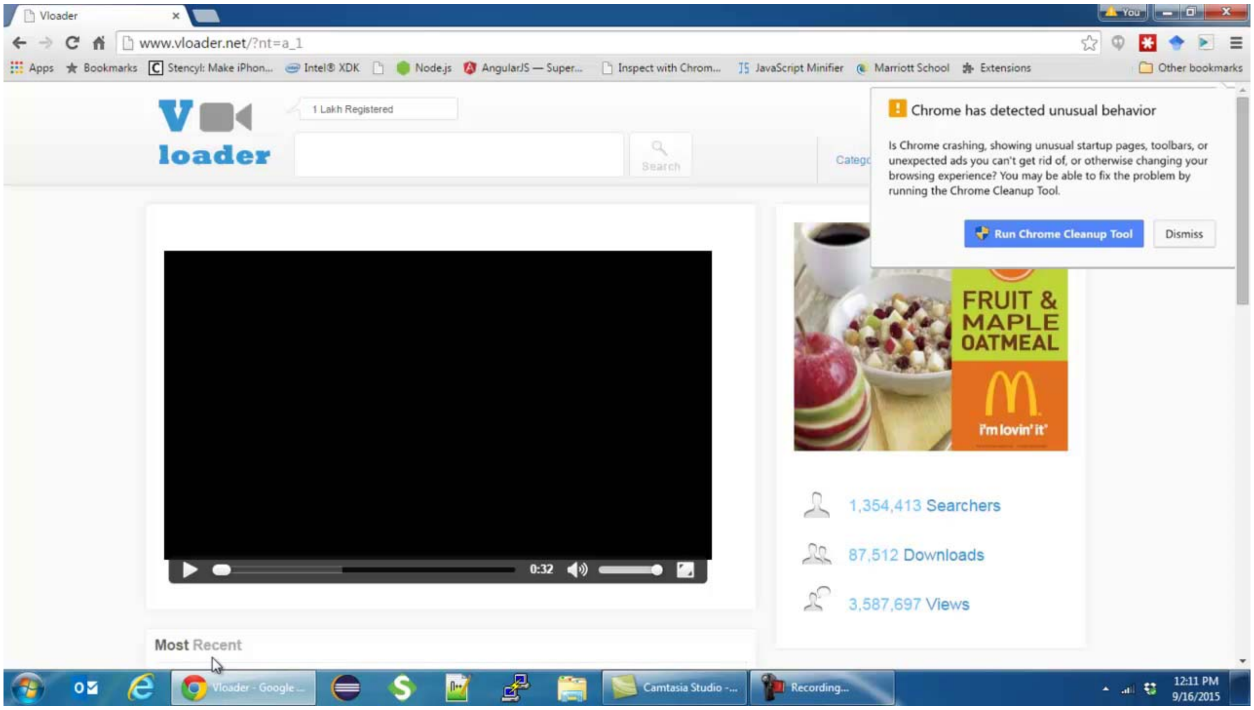


Figure F6. Low-DTI-2: After video.

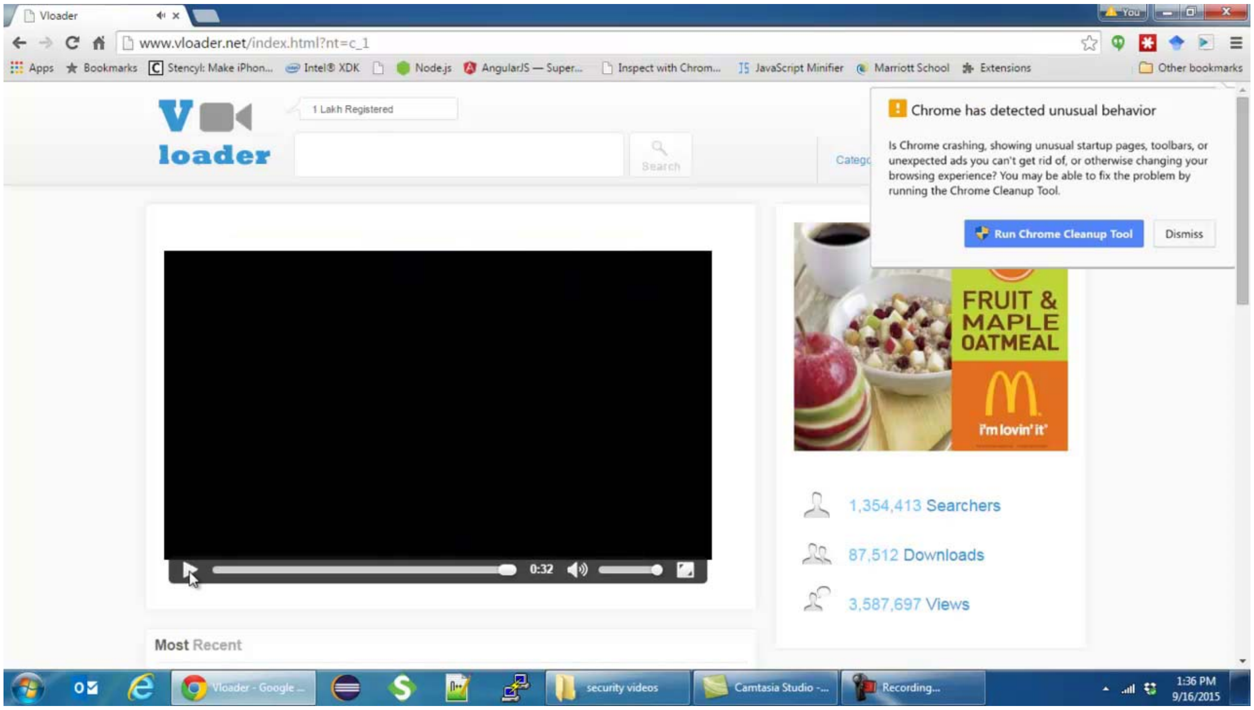


Figure F7. Low-DTI-3: Immediately after switching web domains.

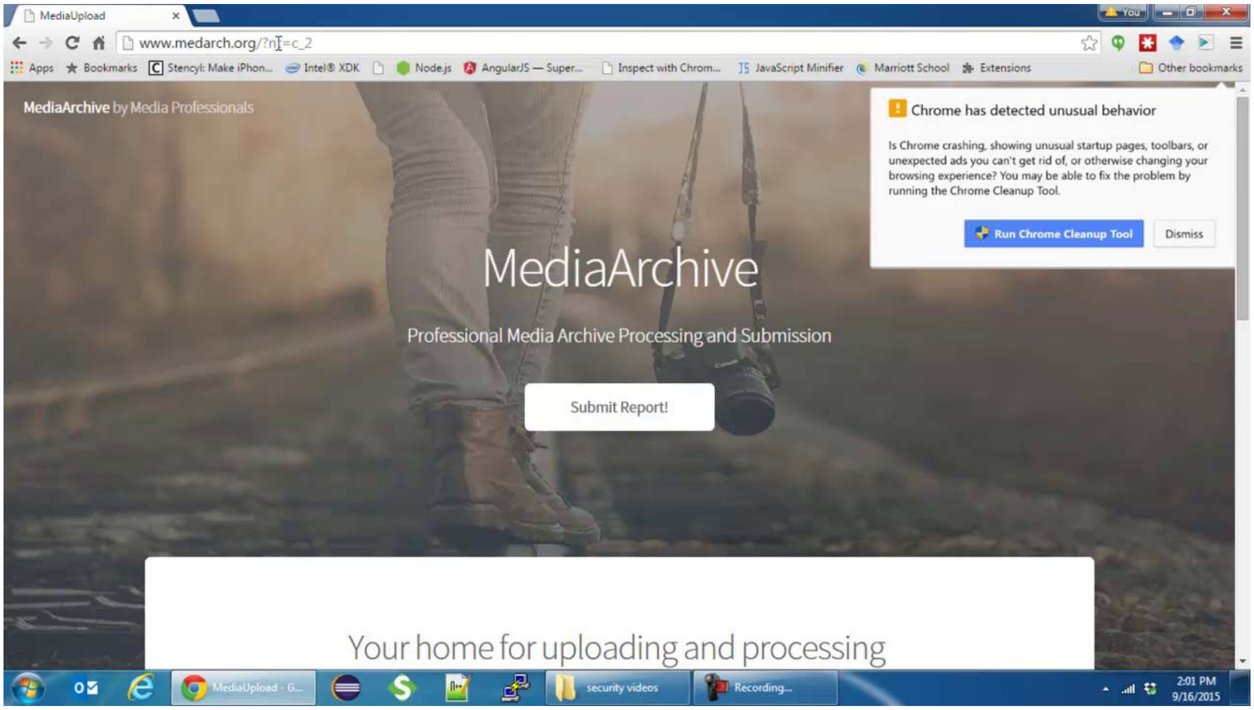


Figure F8. Low-DTI-4: Waiting for web-based task to complete.

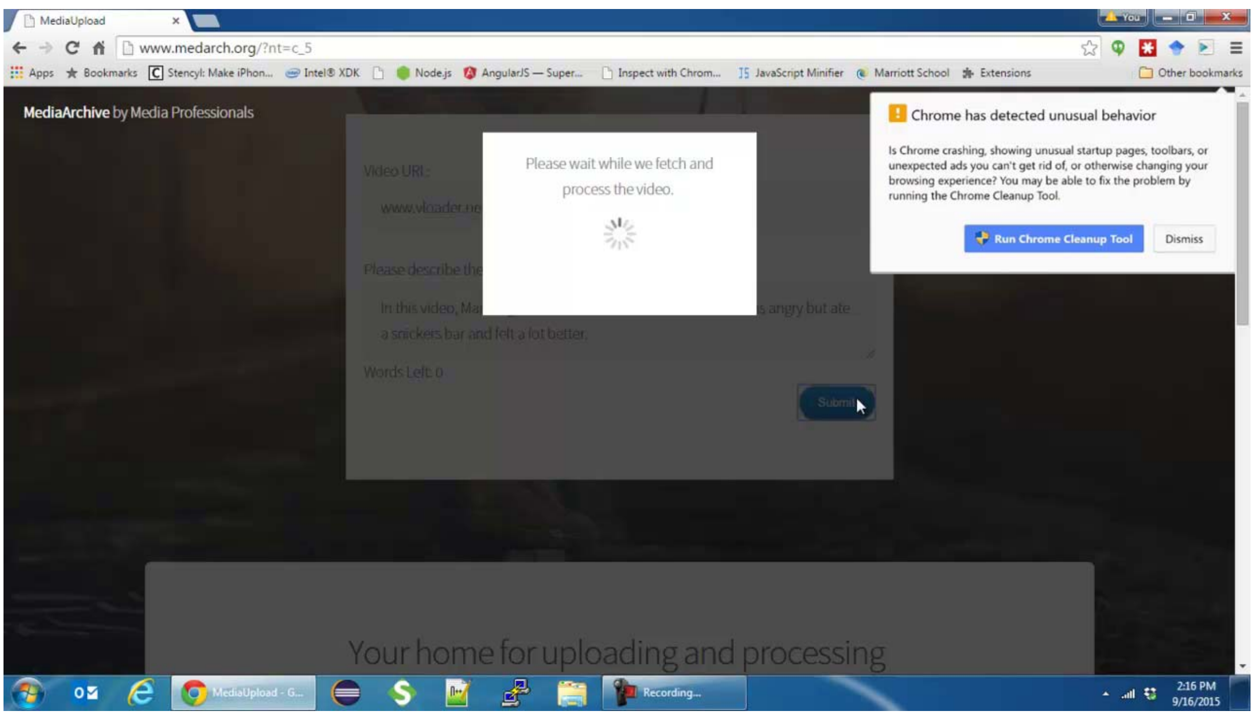
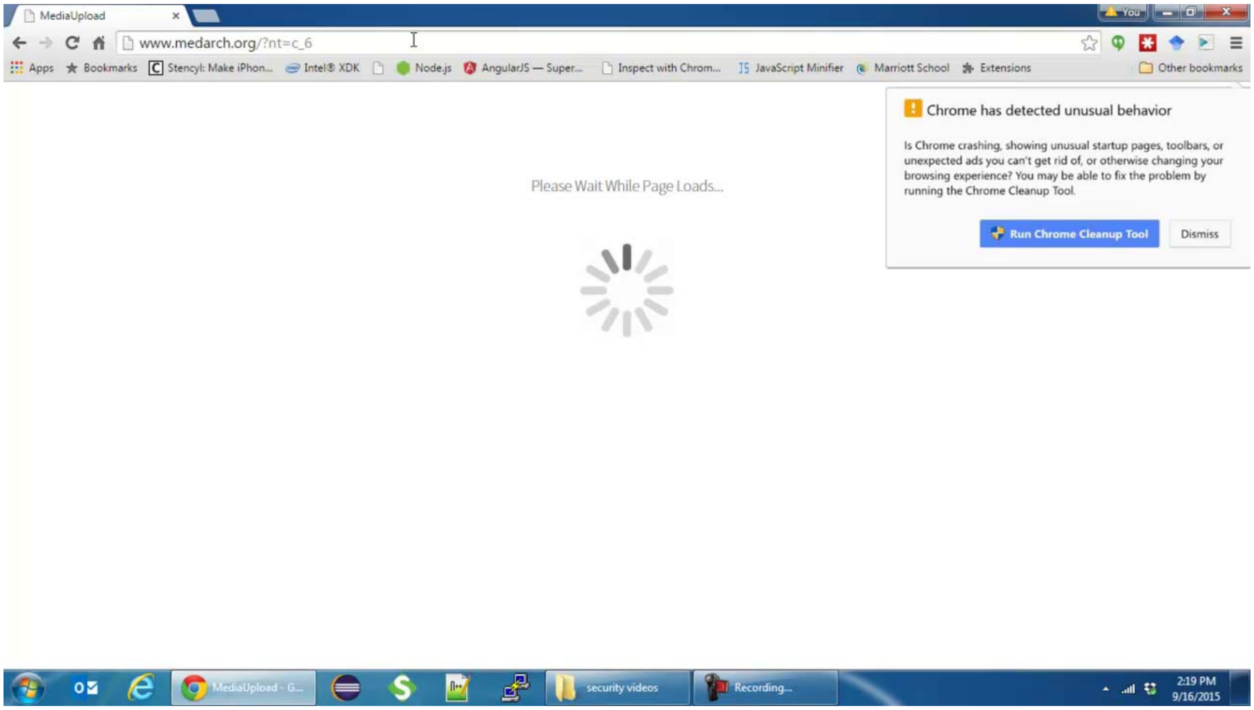


Figure F9. Low-DTI-5: Waiting for page load.



Appendix G. History of Mouse-Cursor Tracking

Origins in Hand and Finger Tracking Research

As a measure of neuromotor and psychological outcomes, mouse cursor tracking fits within the larger domain of hand and finger tracking research. The tracking of the hand and fingers (i.e., fine motor movements) has long been used to provide insight into human cognitive processes. A 1961 review of fine motor movement tracking as an instrument for psychological experiments described the field as consisting of "several hundred task-oriented tracking" publications (Adams 1961, p. 56). In this early research, custom input devices, such as joy sticks (Taylor and Birmingham 1948) and steering-wheel-like devices (Grossman 1960), were used to measure motor movement characteristics, including precision, speed, manual dexterity, and reaction time, to name a few (see Parker Jr and Fleishman 1960 for a summary). Researchers used these motor movement characteristics to gain insight into various cognitive and neuromotor processes, such as response orientation (Fleishman 1957; Fleishman and Hempel Jr 1956), cognitive integration (Guilford and Lacey 1947), and change anticipation (Poulton 1952).

Mouse Tracking and the Advent of Personal Computing

As the adoption of personal computers (equipped with hand-held input devices, such as the computer mouse) drastically increased in the 1990s and 2000s, so did the opportunities for studying cognitive processes via hand movements. The term "mouse cursor tracking" (sometimes just referred to as "mouse tracking") was coined, referring to the measurement of cursor positions and timestamps of movements on the computer screen (which could be manipulated by the computer mouse or another input device, such as a track pad, pointing stick, or touch screen). Researchers initially explored using mouse cursor tracking as a cost-effective alternative to eye tracking to denote where people devote their attention in a HCI context (Byrne et al. 1999; Chen et al. 2001; Guo and Agichtein 2010). For example, research has shown that eye-gaze and cursor-movement patterns are highly correlated (Chen et al. 2001; Guo and Agichtein 2010; Pan et al. 2004). When scanning search results, the cursor often follows the eye and marks promising search hits (i.e., the cursor pointer stops or lingers near such information), suggesting where users devote their attention (Rodden et al. 2008). Likewise, users often move the cursor while viewing web pages, suggesting that the cursor may indicate where users focus their attention (Mueller and Lockerd 2001). In selecting menu items, the cursor often tags potential targets (i.e., hovers over the link) before selecting an item (Cox and Silva 2006). Monitoring user clicks can also assess the relevance of search results (Huang et al. 2011). Finally, by continuously recording cursor position, researchers can assess the user's awareness, attraction, and avoidance of content (e.g., avoiding ads, not looking at text because of frustration, or struggling reading the text) (Navalpakkam and Churchill 2012). Consequently, mouse cursor tracking is often applied as a usability assessment tool for visualizing cursor movements on web pages (Arroyo et al. 2006; Lagun and Agichtein 2011) and developing heat maps that indicate where users devote their attention (Atterer and Lorenzi 2008; Lettner and Holzmann 2012).

Advancement of Mouse Tracking as a Neurophysiological Method

As the ability to assess more fine-grained measurements and mouse cursor movements improved, research expanded the use of mouse cursor tracking to explore a more diverse set of neuromotor and psychological responses. In a concise review of mouse cursor-tracking literature, Freeman et al. (2011, p. 1) suggested that the movements of the hand "offer continuous streams of output that can reveal ongoing dynamics of processing, potentially capturing the mind in motion with fine-grained temporal sensitivity." Accordingly, hundreds of recent studies have chosen mouse cursor tracking as a methodology for studying various cognitive and emotional processes (see Table G1 for recent examples). Many of these studies have focused on how people respond immediately after seeing a stimulus and the cognitive process of decision-making.

Table G1. **Examples of recent cognitive and emotional processes examined through monitoring mouse cursor/hand movements.**

Cognitive process examined through mouse cursor/hand movements	Citation
Attitude formation, concealment of racial prejudices	(Wojnowicz et al. 2009)
Attraction toward distracting stimuli	(Song and Nakayama 2006; Song and Nakayama 2008)
Decision conflict	(McKinstry et al. 2008; Palmer et al. 2013)
Decision making	(Dshemuchadse et al. 2013; Martens et al. 2012)
Deception	(Duran et al. 2010; Weis 2012)
Detection of dual cognitive processing	(Freeman and Dale 2012)
Dynamic competition in classification tasks	(Dale et al. 2007; Freeman and Ambady 2009; Freeman and Ambady 2011; Freeman et al. 2008)
Emotional reactions	(Hibbeln et al. forthcoming; Maehr 2008; Rodrigues et al. 2013; Zimmermann et al. 2006; Zimmermann et al. 2003)
Increased cognitive processing	(Freeman and Ambady 2011)
Language learning, processing, or interpretation	(Barca and Pezzulo 2012; Bartolotti and Marian 2012; Farmer et al. 2007; Spivey et al. 2005)
Learning	(Dale et al. 2008; Zushi et al. 2012)
Mathematical processing	(Faulkenberry 2013)
Memory recall	(Papesh and Goldinger 2012)
Metacognition	(Metcalfe et al. 2013)
Perception formation of people	(Cloutier et al. 2014; Freeman 2014)
Semantic priming	(Shah et al. 2014)
Search/Recognition	(Solman et al. 2012)
Spatial knowledge development	(Wang et al. 2012)
Subconscious/Implicit/Anticipatory processing	(Bruhn 2013; Tower-Richardi et al. 2012; Yu et al. 2012)
Task switching	(Weaver and Arrington 2013)

How Mouse Cursor Tracking is Commonly Implemented

Mouse cursor tracking is typically performed by embedding JavaScript into a web page (e.g., JQuery) or by using a desktop application, such as MouseTracker (Freeman and Ambady 2010). For example, JQuery (a common and freely available JavaScript library) can capture the x, y coordinate and timestamp for mouse cursor movements on the computer screen. Various statistics can be calculated on the characteristics of trajectories and movements to learn about cognitive and neuromotor processes from this voluminous raw data. For example, characteristics of the trajectory include the x- and y-locations of the cursor during different points of the interaction, the number of direction changes along the trajectory, or the deviation from an idealized response trajectory (a straight line connecting the starting and ending points of a movement). Two measures of deviation from the idealized response trajectory include area-under-the-curve (the geometric area between the idealized response trajectory and the actual trajectory; AUC) and maximum deviation (the longest perpendicular line between the idealized response trajectory and the actual trajectory). Examples of movement characteristics include the speed, the acceleration at different points, and the angle of movement, to name a few. A more exhaustive discussion of mouse cursor-tracking measures and their calculations was presented by (Freeman and Ambady 2010; Hehman et al. 2014).

Pros and Cons of Mouse Cursor Tracking

Mouse cursor tracking has pros and cons as a research instrument. The method allows researchers to model many aspects of attention, but it cannot completely replace gaze captured through an eye tracker. For example, a user's eye-gaze fixation may change (move to another stimulus that catches their attention) without moving the mouse. In such circumstances, although a prolong eye-gaze fixation may indicate attention or interest, a prolonged cursor fixation may not (Huang et al. 2012).

On the other hand, mouse cursor tracking can be performed at almost no cost using free JavaScript libraries that can be embedded in normal web pages. Furthermore, mouse cursor tracking can be performed in a natural environment, such as the user's personal computer as he or she interacts with websites, thereby improving the ecological validity of the research. Further, as previously discussed, analyzing mouse cursor movements may provide insights into cognitive process aside from attention (e.g., decision conflict, emotion, memory recall). Hence, mouse cursor tracking has been described as measuring "high-fidelity, real-time motor traces of the mind [that] can reveal 'hidden' cognitive states that are otherwise not availed by traditional measures" (Freeman et al. 2011, p. 2).

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