

## TUNING OUT SECURITY WARNINGS: A LONGITUDINAL EXAMINATION OF HABITUATION THROUGH fMRI, EYE TRACKING, AND FIELD EXPERIMENTS

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## Appendix A

### Theoretical and Methodological Background of Habituation

#### *Habituation and Habit Compared*

Although the words have the same Latin root, the construct of habituation is very different from the construct of habit. *Habit* is defined as “learned sequences of acts that have become automatic responses to specific cues, and are functional in obtaining certain goals or end-states” (Verplanken and Aarts 1999, p. 104). Further, habits are “created by frequently and satisfactorily pairing the execution of an act in response to a specific cue” (Verplanken and Orbell 2003, p. 1314). These descriptions show that habit occurs at the behavioral level and is a form of associative learning, in which behaviors are associated with specific outcomes.

Habituation, in contrast, occurs at the neurobiological level (Ramaswami 2014); it is a form of nonassociative learning, in which an organism filters out stimuli that in the past have not led to relevant outcomes (Rankin et al. 2009). Further, habituation does not require subsequent behavior but occurs involuntarily, that is, without conscious awareness. Indeed, habituation and habit correspond with opposite ends of the C–HIP model: the “attention” and “behavior” stages, respectively. Although habitual behavior is also relevant to security warnings, we restrict our focus to habituation in this study.

#### *What Is Habituation?*

Habituation is widely recognized as “the simplest and most basic form of learning” (Rankin 2009, p. 125); it is believed to be ubiquitous in the animal kingdom, having been found “in every organism studied, from single-celled protozoa, to insects, fish, rats, and people” (Rankin 2009, p. 125; see also Christoffersen 1997). In contrast to associative learning, in which a response to stimulus is associated with another stimulus (e.g., Pavlovian conditioning), habituation is a form of nonassociative learning, because an organism undergoing habituation adjusts the way in which it responds to a stimulus without pairing it with another stimulus, such as a specific consequence (Çevik 2014).

Habituation is an important survival mechanism because it allows organisms to filter out stimuli in the environment that are not relevant, thus conserving energy to respond to stimuli that predict things that are good or bad for survival (Schmid et al. 2014). Not surprisingly, humans exhibit habituation to a wide variety of stimuli—visual, auditory, and others—and it is evident as early as infancy (Colombo and Mitchell 2009).

### **Repetition Suppression: A Neurobiological View of Habituation**

A neural manifestation of habituation to visual stimuli in the brain is called *repetition suppression* (RS): the reduction of neural responses to stimuli that are repeatedly viewed (Grill-Spector et al. 2006). RS has been observed in a range of neural measurement techniques, including single-cell recording (Kaliukhovich and Vogels 2010), functional magnetic resonance imaging (fMRI) (Hawco and Lepage 2014; Summerfield et al. 2008; Vidyasagar et al. 2010), electroencephalography (EEG) (Summerfield et al. 2011), and magnetoencephalography (MEG) (Todorovic and de Lange 2012). Researchers have observed activation decreases for repeated stimuli at delays ranging from mere milliseconds to days (Grill-Spector et al. 2006; van Turenout et al. 2000).

Despite the robustness of the findings on RS, debate continues on the neural and cognitive reasons for reduced neural responses to repeated stimuli and how they relate to long-term behavioral habituation. The two most prevalent (and opposing) explanations for RS are the bottom-up and top-down models (Valentini 2011). According to the bottom-up (or fatigue) model, RS is due to the refractory period of local neural generators in response to physical stimulation (Grill-Spector et al. 2006). In contrast, the top-down (or predictive coding) model holds that RS is not local in nature but instead is due to higher levels of cognition wherein the brain determines the expected probability with which a stimulus will occur (Mayrhauser et al. 2014). Recent research suggests that RS is likely a result of a combination of the bottom-up and top-down mechanisms (Hsu et al. 2014; Mayrhauser et al. 2014; Valentini 2011).

### **Eye Movement-Based Memory: An Eye Tracking-Based View of Habituation**

Another manifestation of habituation is the eye movement–based memory (EMM) effect (Ryan et al. 2000). The EMM effect is apparent in fewer eye-gaze fixations and less visual sampling of the regions of interest within the visual stimulus. Memory researchers have discovered that the EMM effect is a pervasive phenomenon in which people unconsciously pay less attention to images they have viewed before. With repeated exposure, the memories become increasingly available, thus requiring less visual sampling of an image (Heisz and Shore 2008). People’s attention fundamentally decreases in a systematic fashion with repeated viewings, even when they do not consciously recognize that they have seen an image before (Hannula et al. 2010). For these reasons, the EMM effect is a robust means of directly observing habituation to security warnings and of evaluating warning designs intended to reduce its occurrence.

## **Appendix B**

### **fMRI and Eye-Tracking Experimental 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 various tasks. Structural images for spatial normalization and overlay of functional data were acquired with a T1-weighted magnetization-prepared rapid gradient-echo (MP-RAGE) sequence with the following parameters: matrix size = 224 × 256; TR = 1900 ms; TE = 2.26 ms; field of view = 219 × 250 mm; NEX = 1; slice thickness = 1.0 mm; voxel size = 1 × .977 × .977 mm<sup>3</sup>; flip angle = 9°; number of slices = 176. Functional scans were acquired with a T2\*-weighted gradient-echo echoplanar pulse sequence with the following parameters: matrix size = 64 × 64; field of view = 192 mm; slice thickness = 3 mm; TR = 2000 ms; 229 TRs; TE = 28 ms; number of slices = 39; voxel size = 3 × 3 × 3 mm; flip angle = 90°. Slices were aligned parallel with the rostrum and the splenium of the corpus callosum. The first three volumes acquired were discarded to allow for T1 stabilization.

Eye-tracking data were collected on each scan using an MRI-compatible SR Research EyeLink 1000 Plus long-range eye tracker (see Figure B2) with a spatial resolution of 0.01° and sampling at 1,000 Hz. Eye movements were recorded for the right eye. A nine-point calibration routine was used to map eye position in order to screen coordinates prior to each scanning block. Eye-fixation data were processed with DataViewer software (SR Research Ltd., version 1.11.900) to identify fixations and saccades. *Saccades* were defined as eye movements that

met three parameters: eye movement of at least  $.1^\circ$ , velocity of at least  $30^\circ/\text{second}$ , and acceleration of at least  $8,000^\circ/\text{second}$ . *Fixations* were defined as periods of time that were between the saccades and that were not part of blinks. Image size was normalized to subtend approximately  $8.5^\circ$  of the visual angle on the images' longest axis.

### **Engagement Check**

To ensure that participants were attentive to the task in the scanner, they were instructed to rate the severity of the content of each item as it was presented to them; the answer choices available to them were “extremely severe,” “somewhat severe,” “somewhat not severe,” and “extremely not severe.” Answers were given any time during each trial by pressing a button on an MRI-compatible button box. Following Dimoka (2012), we performed two checks to ensure that participants were engaged in the task. First, we explored whether participants ranked each stimulus on the severity scale or ignored the ranking. We found that participants ranked stimuli 99.8% of the time, which is a strong indicator of engagement. Second, we explored whether participants ranked the security warnings as more severe than the software prompts, which would suggest that participants were giving thoughtful responses. A *t*-test indicated that participants did indeed report that the security warnings ( $m = 2.998$ ,  $SD = 1.478$ ) were more severe than the software prompts [ $m = 2.366$ ,  $SD = 1.826$ ],  $t(13463) = 25.236$ ,  $p < .001$ ,  $d = 0.435$ ].

### **fMRI Data Analysis Details**

Functional data were slice-time corrected to account for differences in acquisition time for different slices of each volume; then, each volume was registered with the middle volume of each run to account for low-frequency motion. A three-dimensional automated image registration routine—program 3dVolreg (Cox and Jesmanowicz 1999), which uses Fourier interpolation—was applied to the volumes to realign them with the first volume of the first series used as a spatial reference. Data from each run were aligned with the run nearest in time to the acquisition of the structural scan. The structural scan was then coregistered to the functional scans. Spatial normalization was accomplished by calculating a transformation from each subject's structural scan to a template brain with advanced neuroimaging tools (ANTs) and then applying the transformation to the structural and functional data for each subject. The experimental design is represented pictorially in Figure B1.

Behavioral vectors were created that coded for stimulus type (e.g., security warnings, general software images) and repetition number. These were then entered separately into single-participant regression analyses for each day. Stimulus events were modeled using a stick function convolved with the canonical hemodynamic response. Regressors that coded for motion and scanner drift were also entered into the model as nuisance variables. Spatial smoothing was conducted by blurring the resulting beta values with a 5-mm FWHM Gaussian kernel to increase the signal-to-noise ratio. Beta values for the conditions of interest were then entered into group-level analyses as we tested each hypothesis (below). Group comparisons were corrected for multiple comparisons using a voxel-wise threshold of  $p < .02$  and a spatial-extent threshold of 40 contiguous voxels ( $1080 \text{ mm}^3$ ) for an overall corrected  $p$ -value  $< .05$ , as determined through Monte Carlo simulations (Xiong et al. 1995).

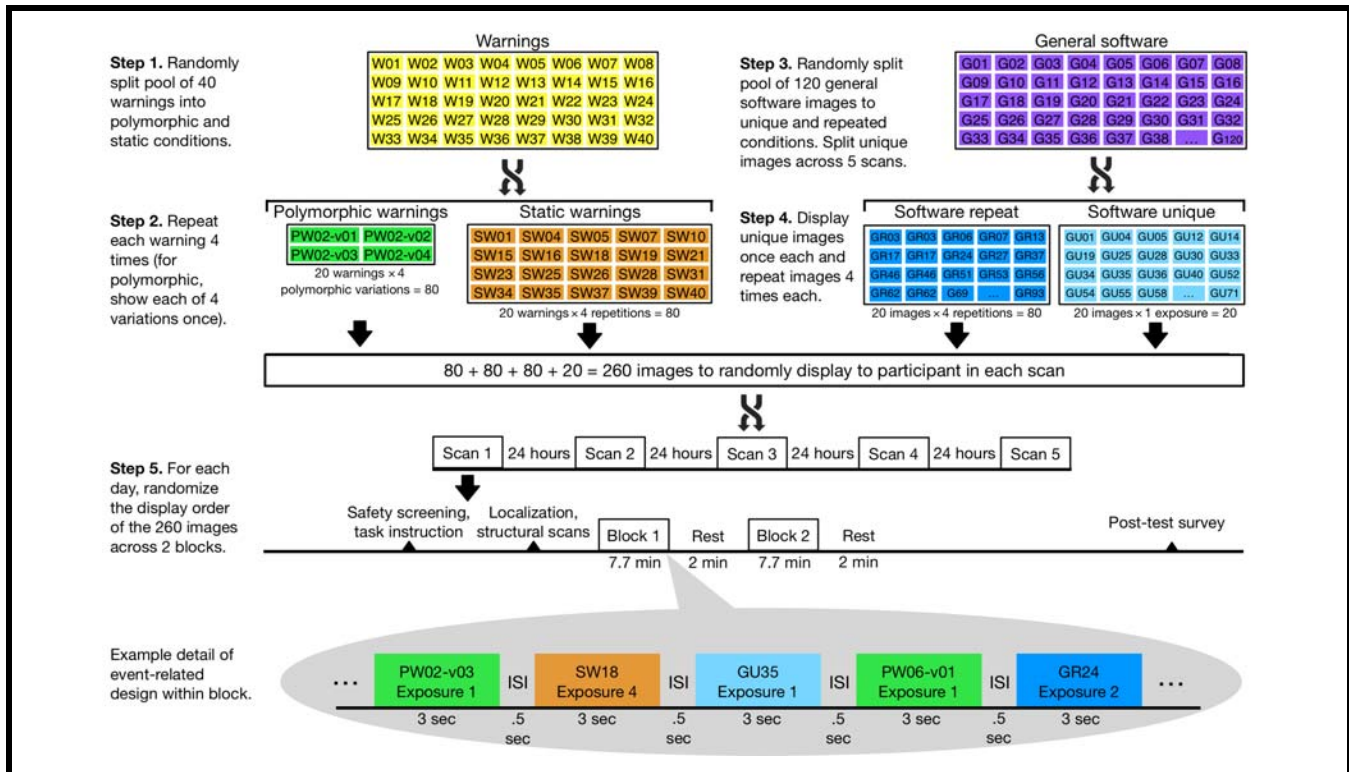


Figure B1. fMRI Repetition-Suppression-Effect (RSE) Longitudinal Protocol

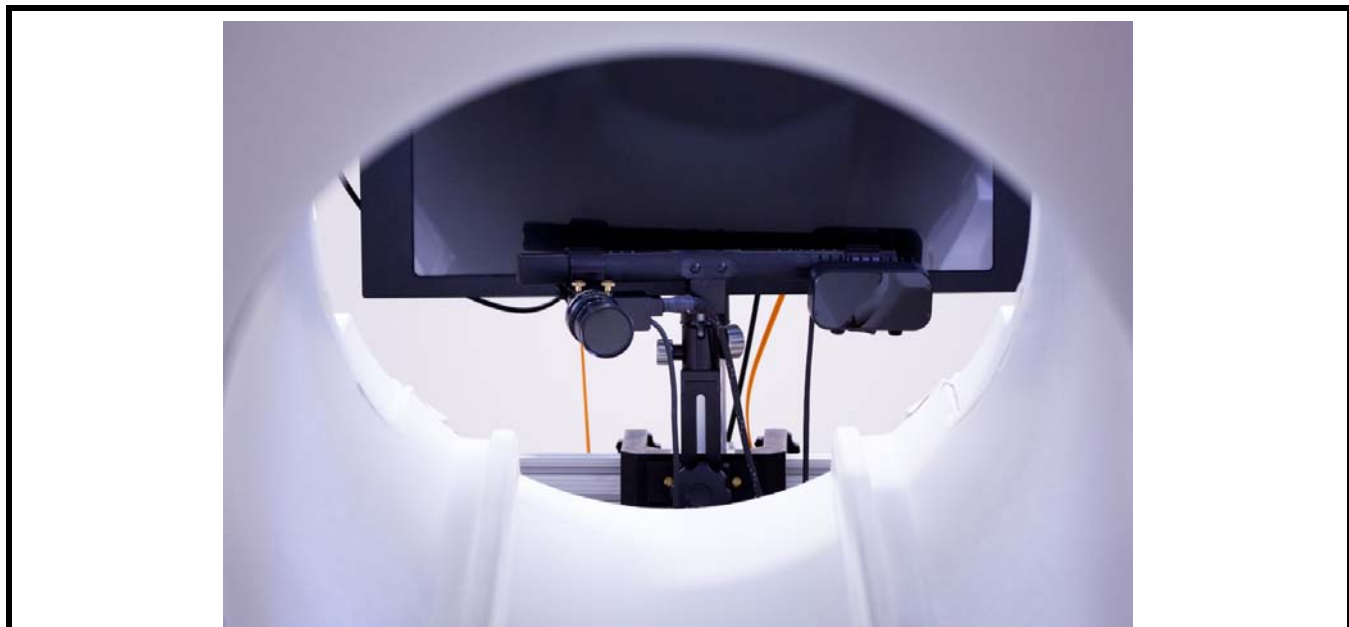


Figure B2. EyeLink 1000 Plus Long-Range Eye Tracker (mounted under the MRI viewing monitor)

# Appendix C

## Supplemental Analysis of Fixation Duration

In our main analysis, we tested the hypotheses with the eye-tracking data, using fixation count as the dependent variable. As a supplemental analysis, we tested our hypotheses using fixation duration, or the total time a person is fixated on a security message, as the dependent variable. The results are summarized below.

### ***H1a Analysis: Users Habituate to Warnings Within an Experimental Session***

We included fixation duration as the dependent variable; the subject ID, day number, and warning ID were included as random factors in a linear mixed-effects model. The presentation number was treated as a fixed factor, and visual complexity<sup>1</sup> was included as a covariate. The analysis supported H1a; the presentation number beta was significantly negative, indicating that habituation had occurred:  $\chi^2(1, N = 11,976) = 174.37, p < .001, \beta = -34.30$ . However, visual complexity was not significant:  $\chi^2(1, N = 11,976) = 2.84, p > .05, \beta = 12.25$ . The  $R^2$  of the model was .386.

### ***H1b Analysis: Users Habituate Less to Polymorphic Warnings than to Static Warnings Within an Experimental Session***

We specified the same mixed-effects model as in H1a, except that we included an interaction term between presentation number and determination of whether the warning was polymorphic. If the interaction was significantly positive, this would indicate that the participants habituated less to polymorphic warnings. The eye-tracking analysis supported H1b. Both main effects for presentation number [ $\chi^2(1, N = 11,976) = 132.89, p < .001, \beta = -42.26$ ] and polymorphism [ $\chi^2(1, N = 11,976) = 5.62, p < .01, \beta = -33.60$ ] were significant; in addition, the interaction was significant:  $\chi^2(1, N = 11,976) = 2.95, p > .05, \beta = 15.94$ . Visual complexity was not significant:  $\chi^2(1, N = 11,976) = 82.79, p < .001, \beta = 12.48$ . The  $R^2$  of the model was .387.

### ***H2a Analysis: Users Habituate to Warnings Across Days***

In the linear mixed-effects model, we included fixation duration as the dependent variable, with the subject ID and warning ID as random factors. The presentation number (across days) was treated as a fixed factor, and visual complexity was included as a covariate. The eye-tracking analysis supported H2a; the beta of presentation number across days was significantly negative [ $\chi^2(1, N = 11,976) = 769.24, p < .001, \beta = -15.35$ ], indicating habituation. Visual complexity was not significant:  $\chi^2(1, N = 11,976) = 2.94, p > .05, \beta = 12.40$ . The  $R^2$  of the model was 0.269.

### ***H2b Analysis: Users Habituate Less to Polymorphic Warnings than to Static Warnings Across Days***

We specified the same mixed-effects model as in H2a, except that we included an interaction term between presentation number (across days) and determination of whether the warning was polymorphic (coded as 1 for polymorphic and 0 for static). The eye-tracking analysis supported H1b; the interaction between presentation number and polymorphic-warning type was significantly positive [ $\chi^2(1, N = 11,976) = 3.25, p < .05, \beta = 1.962$ ], indicating that participants habituated less to polymorphic warnings across days than to static warnings. The main effect for presentation number [ $\chi^2(1, N = 11,976) = 441.44, p < .001, \beta = -16.328$ ] was significant, but the main effect for polymorphism [ $\chi^2(1, N = 11,976) = 1.03, p > .05, \beta = -13.405$ ] was not. Visual complexity was not significant:  $\chi^2(1, N = 11,976) = 3.09, p > .05, \beta = 12.686$ . The  $R^2$  of the model was 0.153.

<sup>1</sup>Visual complexity was calculated using a script in MATLAB (Rosenholtz et al. 2007).

### **H3a Analysis: If Warnings Are Withheld After Habituation Occurs, the Response Recovers at Least Partially the Next Day**

We subtracted the fixation duration for the first viewing of a warning on a day from the fixation duration for the last viewing of the warning on the previous day. We then conducted a *t*-test to test this hypothesis. The analysis supported H3a; participants experienced significant positive recovery ( $m = 35.887$ ,  $SD = 483.903$ ) from day to day:  $t(2288) = 3.5482$ ,  $p < .001$ ,  $d = 0.148$ .

### **H3b Analysis: If Warnings Are Withheld After Habituation Occurs, Response Recovery Is Stronger for Polymorphic Warnings than for Static Warnings the Next Day**

We again subtracted the fixation duration for the first viewing of a warning on a day from the fixation duration for the last viewing of the warning on the previous day. We then specified a linear mixed-effects model that tested whether warning type (polymorphic versus static) predicted this difference. The subject ID, day interval (e.g., the difference between day 1 and day 2 was coded as 1), and warning ID were included as random factors. Polymorphism (coded as 1 for polymorphic and 0 for static) was included as a fixed factor, and visual complexity was included as a covariate. The eye-tracking analysis did not support H3b. Neither the warning type [ $\chi^2(1, N = 2,400) = 2.05$ ,  $p > .05$ ,  $\beta = -24.14$ ] nor visual complexity [ $\chi^2(1, N = 2,400) = 3.28$ ,  $p > .05$ ,  $\beta = 18.53$ ] significantly predicted recovery between days.

### **H4a Analysis: The Amount of Recovery Will Decrease Across Days**

We again used the difference in the fixation duration for the last viewing of the warning on the previous day as our dependent variable. We specified a mixed-effects model that tested whether the day interval (e.g., 1 for the difference between days 1 and 2) predicted this difference. The subject ID and warning ID were included as random factors. The day interval was treated as a fixed factor, and visual complexity was included as a covariate. The eye-tracking analysis supported H4a. The day interval was significantly negative [ $\chi^2(1, N = 2,400) = 9.77$ ,  $p < .001$ ,  $\beta = -27.73$ ], indicating that recovery decreased across days. Visual complexity was not significant:  $\chi^2(1, N = 2,400) = 3.39$ ,  $p > .05$ ,  $\beta = 18.75$ . The  $R^2$  of the model was .079.

### **H4b Analysis: The Amount of Recovery Will Decrease Less for Polymorphic Warnings than for Static Warnings Across Days**

We specified the same linear mixed-effects model as in H4a, except that we included an interaction term between day intervals (the difference between days) and another term for whether the warning was polymorphic (coded as 1 for polymorphic and 0 for static). The eye-tracking analysis did not support H4b. The main effect for day number [ $\chi^2(1, N = 2,400) = 7.05$ ,  $p > .01$ ,  $\beta = 33.25$ ] was significant. However, the main effect for polymorphism [ $\chi^2(1, N = 2,400) = 0.01$ ,  $p > .05$ ,  $\beta = -4.86$ ] and for the interaction were nonsignificant:  $\chi^2(1, N = 2,400) = 0.40$ ,  $p > .05$ ,  $\beta = -11.12$ . Likewise, visual complexity was nonsignificant:  $\chi^2(1, N = 2,400) = 2.93$ ,  $p > .05$ ,  $\beta = 17.48$ . Table C1 compares the results for fixation count, fixation duration, and fMRI data.

**Table C1. Summary of Results**

<b>Hypothesis</b>	<b>Fixation Count</b>	<b>Fixation Duration</b>	<b>fMRI</b>
H1a: Users habituate to warnings within an experimental session.	Supported	Supported	Supported
H1b: Users habituate less to polymorphic warnings than to static warnings in an experimental session.	Supported	Supported	Supported
H2a: Users habituate to warnings across days.	Supported	Supported	Supported
H2b: Users habituate less to polymorphic warnings than to static warnings across days.	Supported	Supported	Supported
H3a: If warnings are withheld after habituation occurs, the response recovers at least partially the next day.	Supported	Supported	Supported
H3b: If warnings are withheld after habituation occurs, response recovery is stronger for polymorphic warnings than for static warnings the next day.	Not supported	Not supported	Not supported
H4a: The amount of recovery will decrease across days.	Supported	Supported	Not supported
H4b: The amount of recovery will decrease less for polymorphic warnings than for static warnings across days.	Not supported	Not supported	Not supported

# Appendix D

## Polymorphic Warning Variations Used in Experiment 2

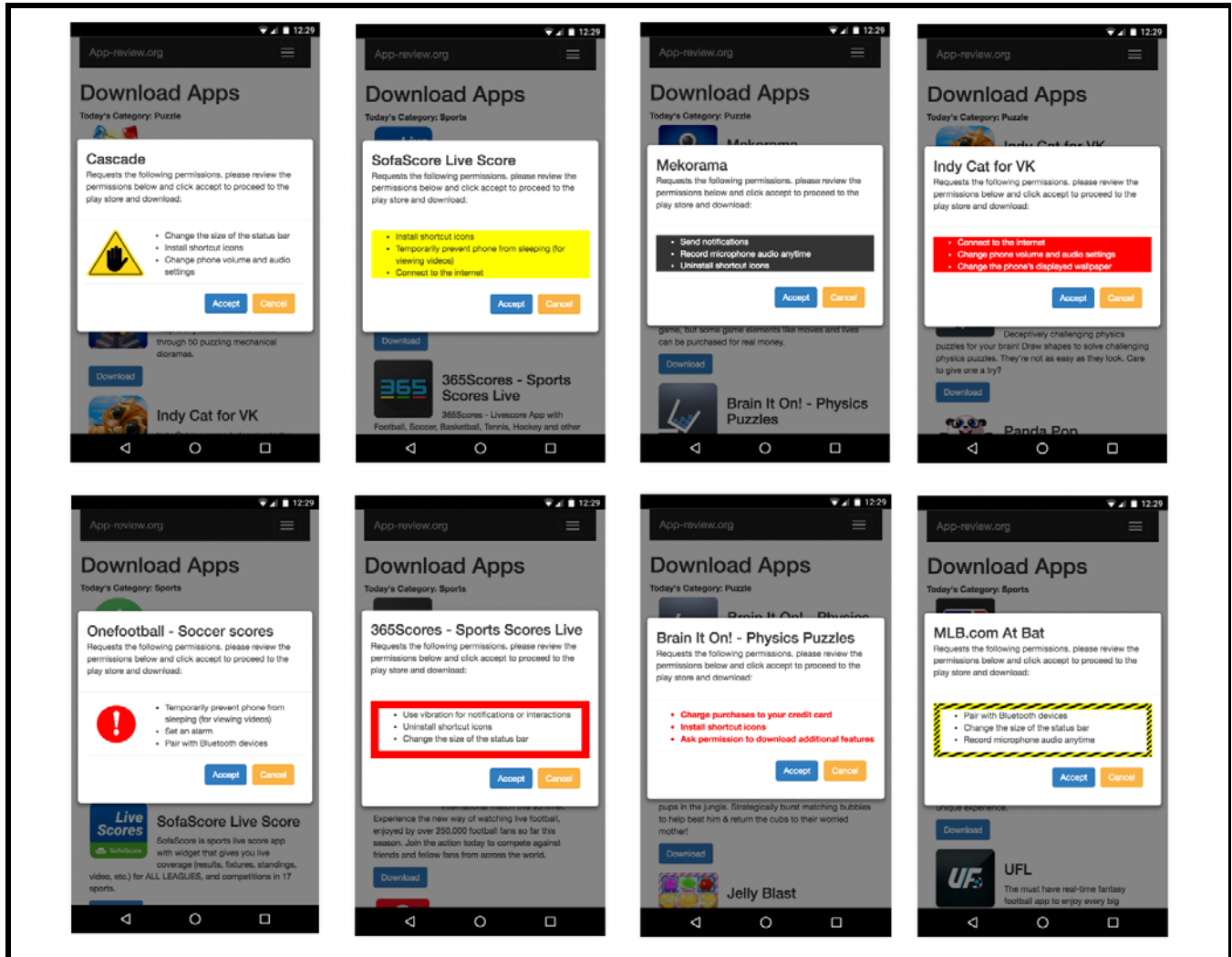


Figure D1. Nonanimated Polymorphic Variations



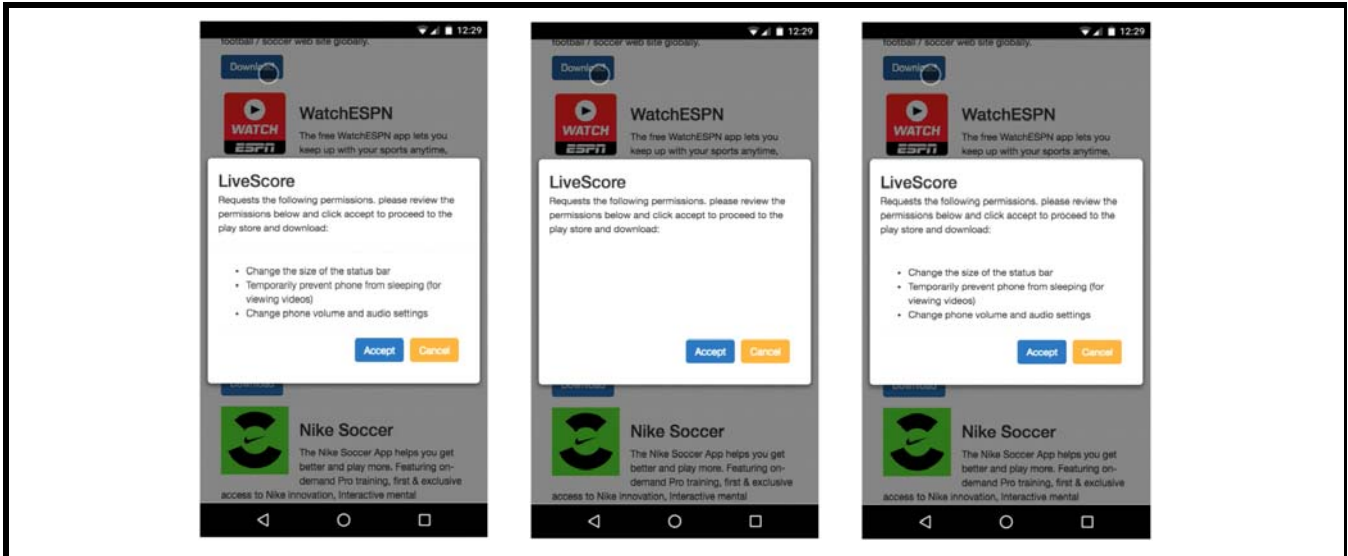


Figure D2. Animated Polymorphic Variation: Flash

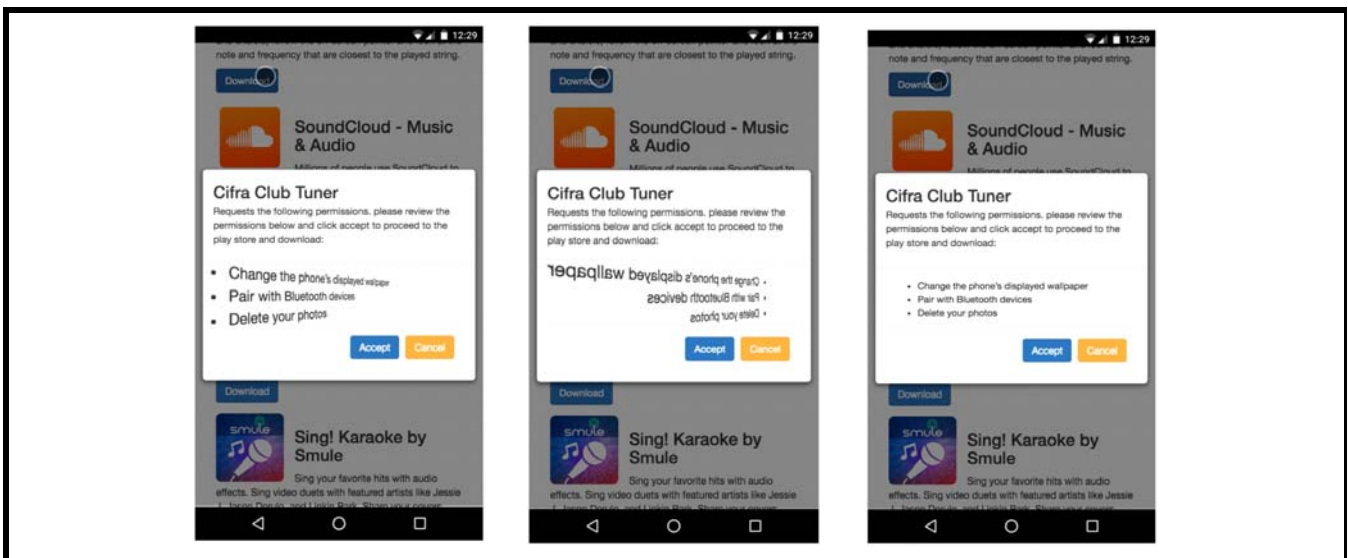


Figure D3. Animated Polymorphic Variation: Flip

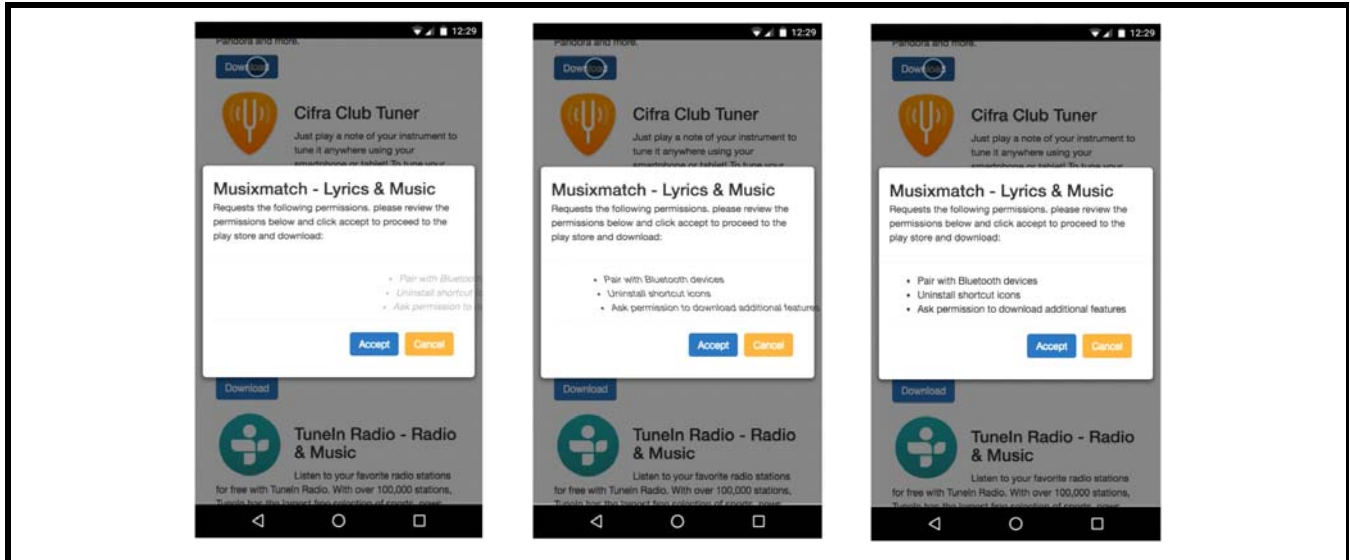


Figure D4. Animated Polymorphic Variation: "Light Speed In"

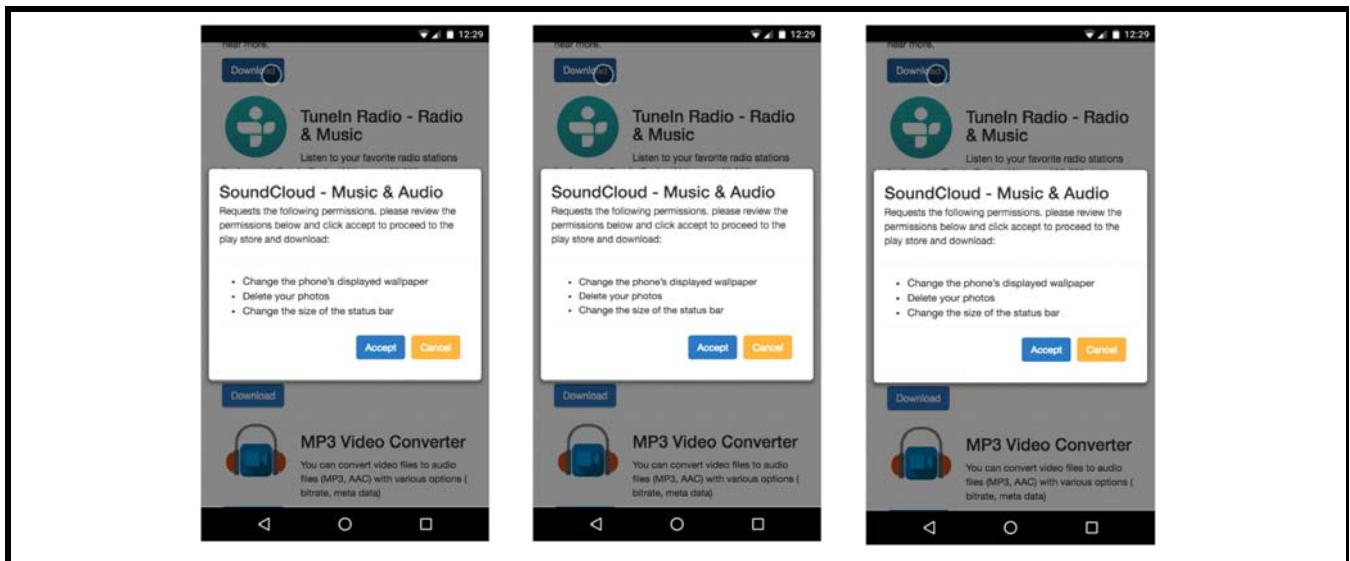


Figure D5. Animated Polymorphic Variation: Pulse

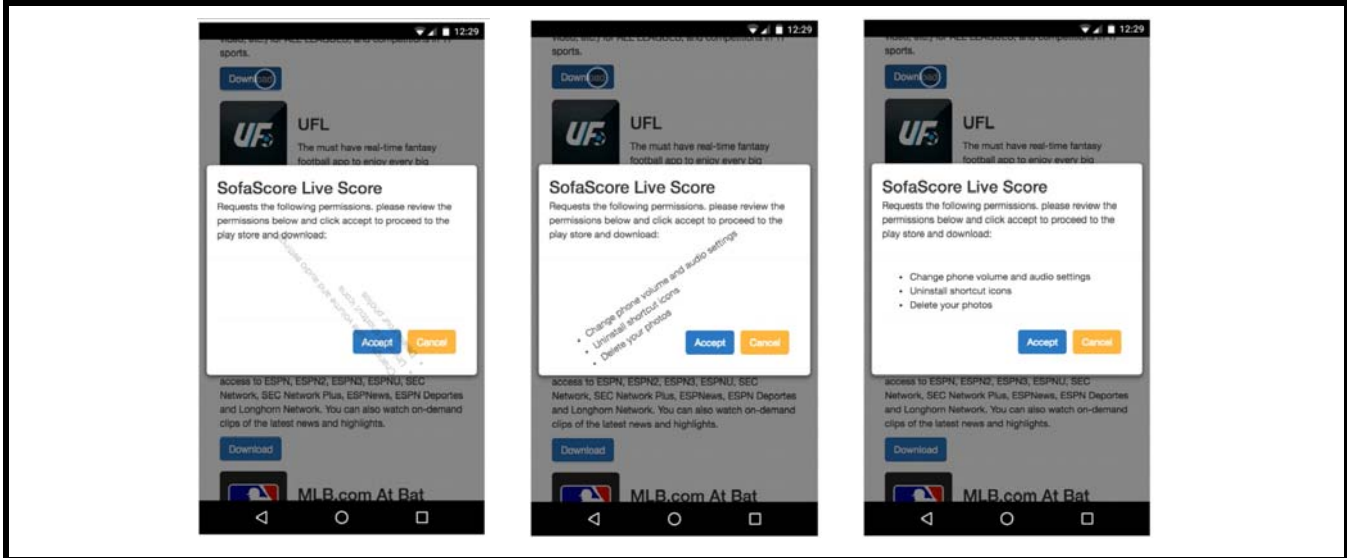


Figure D6. Animated Polymorphic Variation: “Rotate In”

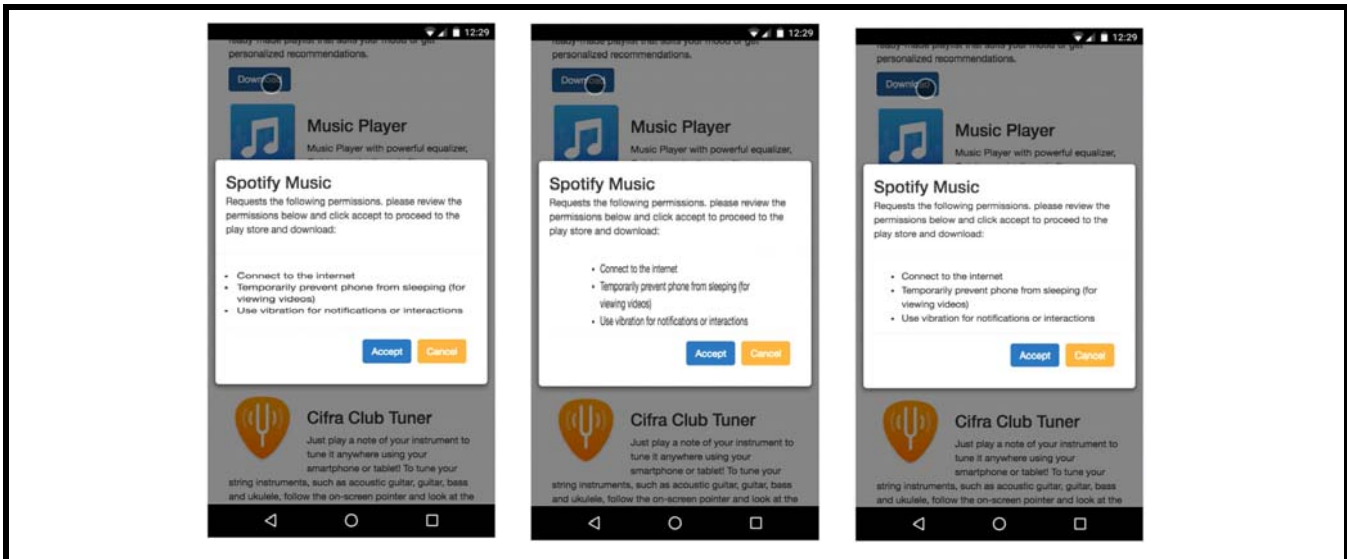


Figure D7. Animated Polymorphic Variation: “Rubber Band”

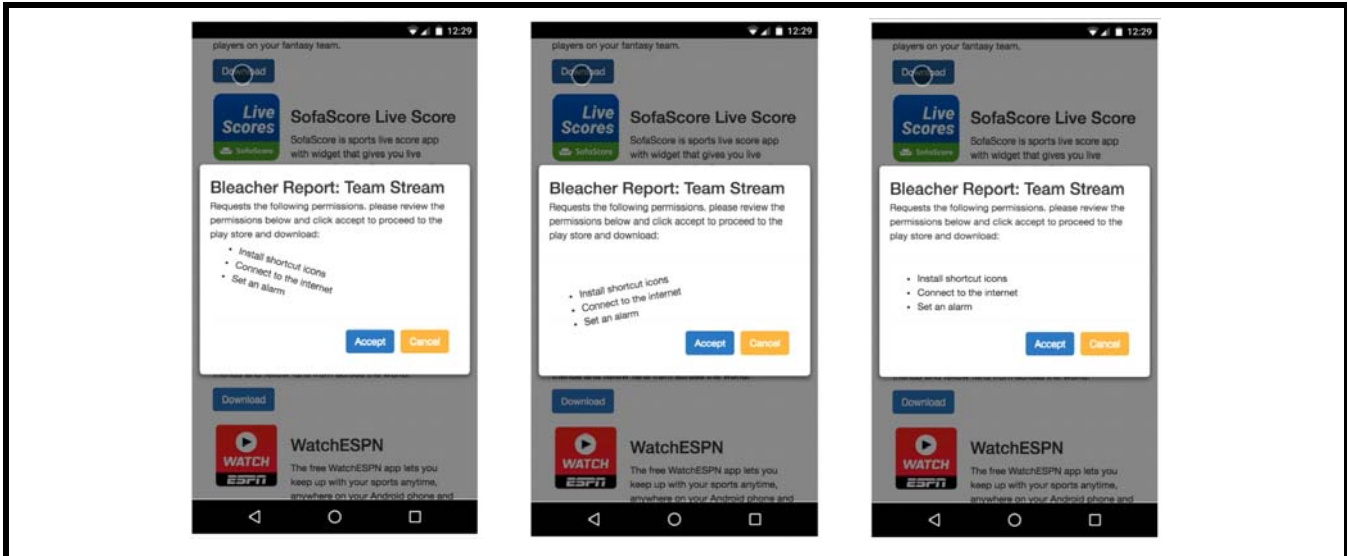


Figure D8. Animated Polymorphic Variation: Swing

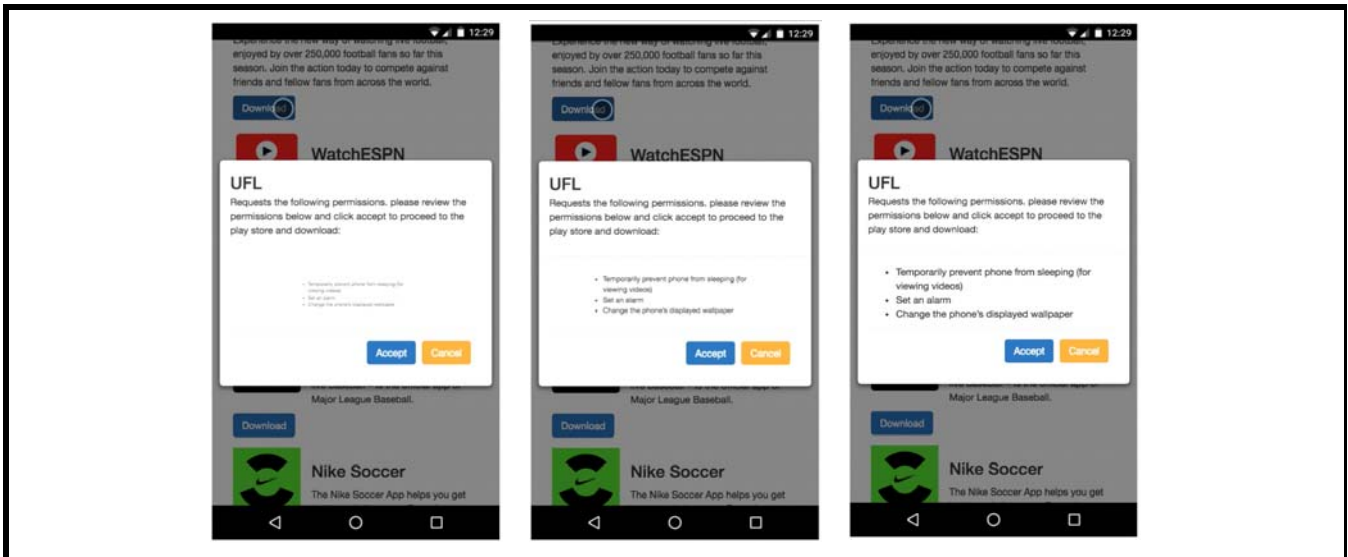


Figure D9. Animated Polymorphic Variation: “Zoom In”

## Appendix E

### NeuroIS Contributions of Experiment 1

Experiment 1 used fMRI to measure underlying brain activity when individuals were presented with warning messages. As with any research method, the use of fMRI has both strengths and weaknesses. It is important to consider both, along with the purpose of the study, when evaluating the methodology of the experiment.

In information systems research, neurobiological methods can contribute to a deeper understanding of hidden (automatic or unconscious) mental processes; these mental processes are one of seven research opportunities for NeuroIS suggested by Dimoka et al. (2011). Habituation is one such mental process that does not require the conscious awareness of the organism (Groves and Thompson 1970; Sokolov 1963). As such, self-report measures are not useful because users may not even recognize that the process of habituation is occurring (Dimoka et al. 2011; Riedl and Léger 2016; vom Brocke et al. 2013).

Further, although behavioral methods can provide evidence that the artifact reduces warning adherence behavior, these approaches are not able to reveal the extent to which habituation in the brain plays a part in this behavior. Therefore, the use of fMRI yields deeper insights by moving past conscious experience toward looking at the neurobiological processes that are involved (Riedl and Léger 2016). fMRI allows the examination of neuronal processes through the blood oxygen level-dependent (BOLD) response, which is correlated with neuronal activation (Goense and Logothetis 2008), giving an accurate picture of which structures are involved and allowing for inferences about what to manipulate in the IT artifact. In Experiment 1, for example, we confirmed that even with long-term habituation, visual processing areas of the brain show strong habituation effects. Such a finding shows that users are not merely disregarding a warning when they are presented with it; they may not even notice that a warning is novel. This finding lends support to the need for a visual change in the IT artifact (Riedl and Léger 2016).

Finally, existing sources of data—in this case, eye tracking—were complemented in Experiment 1 with brain imaging data, another of the seven research opportunities enjoined by Dimoka et al. (2011). Although eye tracking has been used before to examine habituation to warnings in a cross-sectional experiment (Anderson et al. 2016), Experiment 1 contributes by having simultaneously collected eye-tracking and neuroimaging data over a five-day period. We found that the eye-tracking results closely mimicked the fMRI results, suggesting that eye tracking is a valid index of the mental process of habituation. This suggests that eye tracking is a cost-effective alternative to fMRI for studying habituation to warnings as a mental process, enabling future researchers to conduct less intrusive habituation studies that use eye tracking in a normal computing environment.

## Appendix F

### Ecological Validity Limitations of Experiment 1

The objective of Experiment 1 was to evaluate habituation of attention in the brain in response to static and polymorphic warnings. Accomplishing this purpose required a controlled laboratory setting to enable a precise test of habituation theory, as well as the use of an MRI scanner. The results of Experiment 1 provide unique insights that would not be possible using traditional behavioral methods, as explained in Appendix E. However, these neural insights come at the expense of ecological validity, which concerns whether an “effect is representative of what happens in everyday life” (Crano et al. 2015, p. 136).

There are two primary reasons for this tradeoff. The first is inherent in all fMRI studies. As Riedl et al. (2010, p. 255) observed:

During an fMRI experiment, for example, participants are required to lie still on their back within the scanner while their head is restrained with pads to prevent head motion. Within the scanner, participants can use simple devices to react to the stimuli presented by pressing a button (e.g., to state a chosen alternative in a decision task). . . . An fMRI scanner is also relatively noisy, posing a potential distraction and making auditory stimulus presentation difficult. Therefore, experimental situations in fMRI studies are artificial, because in real life, computer users usually sit in front of their computer in a familiar, comfortable, and quiet environment.

This artificiality results in a high degree of intrusiveness compared to traditional behavioral methods or even other NeuroIS methods (Riedl et al. 2014).

The second tradeoff in ecological validity is specific to studying habituation to warnings. As explained in the discussion section, habituation is a neurobiological phenomenon that relies on the number of presentations of a stimulus in a given amount of time (Rankin et al. 2009). Since security warnings are relatively infrequent, displaying many warning presentations in a single experimental session, even if done in a proportionally accurate way (see Figure 16), may result in a pattern of habituation that is not representative of habituation to warnings in real life. This limitation applies to any laboratory experiment of habituation, regardless of whether it uses neuroimaging or traditional behavioral methods.<sup>2</sup> However, this problem is exacerbated by the requirement of the fMRI method for repeated trials of stimuli to ensure a reliable measure of the response (Turner et al. 2013). Repeated trials result in a high number of warnings being displayed in a single laboratory session.

Given the ecological validity limitations of fMRI and NeuroIS in general, Dimoka et al. (2012) recommended that researchers “replicate [NeuroIS experiments] in a more traditional setting and compare the corresponding behavioral responses to test for external validity” (p. 682), adding that “the richness provided by multiple sources of measures can be used to enhance the ecological validity of IS studies” (p. 695). Accordingly, one of our objectives for Experiment 2 was to conduct a realistic field experiment that we could compare against our fMRI experiment. Although the methods, dependent variables, and experimental designs of Experiments 1 and 2 were quite different, the results corroborate each other in terms of (1) the overall pattern of habituation, (2) the effectiveness of polymorphic warnings in reducing habituation, and (3) the effect of recovery between exposure to warnings (see Table 8). We therefore conclude that the results of Experiment 1 are reasonably accurate, despite the issues of ecological validity discussed above.

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