A precise quantification of how prior experience informs current behavior

Michelle R Kramer, Patrick H Cox, Stephen R Mitroff, & Dwight J Kravitz

The George Washington University

Department of Psychology

2125 G Street NW

Washington, DC 20052

Corresponding Author:

Dwight J Kravitz

kravitzd@gwu.edu

Abstract

Human behavior does not exist in a bubble—it is influenced by countless forces, including each individual's current goals, pre-existing cognitive biases, and prior experience. The current project leveraged a massive behavioral dataset to provide a data-driven quantification of the relationship between prior experience and current behavior. Data from two different behavioral tasks (a categorization task and a visual search task) demonstrated that prior history had a precise, systematic, and meaningful influence on subsequent performance. Specifically, the greater the evidence for (or against) all aspects of the current trial, the more (or less) efficient behavior was on that trial. The robust influence of prior experience was present for even distracting and likely unattended information. The ubiquity and consistency of the effect for features both related and unrelated to stimulus presence suggests a domain-general mechanism that increases the efficiency of behavior in contexts that match prior experience. These findings are theoretically important for understanding behavioral adaptation, experimentally powerful for directly addressing effects of previous trials when designing and analyzing research projects, and potentially useful for optimizing behavior in various applied contexts.

Keywords: big data, visual search, decision making, trial sequence effects, statistical learning

Introduction

Perhaps the most important aspect of behavior is its adaptability—becoming increasingly efficient in contexts that can be anticipated from prior experience. Humans constantly extract regularities from their environment to guide their behavior, regardless of whether or not the experienced regularities are actually predictive of the environment. This adaptability is seen in cognitive psychology experiments, where performance on any given trial can be influenced by what happened on previous trials—a phenomenon broadly referred to as *carryover effects* (e.g., Greenwald, 1976). A similar phenomenon, *hysteresis,* refers to the human factors principle that a system (in this case, the human) will respond differently to the same input depending on how the system has been influenced by past events (Farrell, 1999). The concepts of carryover and hysteresis have been applied across many domains of cognitive psychology at varying levels of complexity, from simple motor priming to more nuanced impacts on attention (e.g., Doyen, Klein, Simons, & Cleeremans, 2014; Maljkovic & Nakayama, 1994; Schwiedrzik & Sudmann, 2020; Tipper & Driver, 1988; Tourangeau, Rasinski, Bradburn, & Andrade, 1989).

Perhaps the simplest and most thoroughly characterized effect in which behavior is influenced by prior events is motor priming. When participants are repeatedly required to make the same motor action, efficiency in making that action increases while concomitantly the efficiency of making a different motor action decreases (e.g., Smith, Johnstone, & Barry, 2008; Yashar, Makovski, & Lamy, 2013). Relatedly, there are well-established effects of response set biases (also called *response priming)*, wherein a participant becomes more efficient at responding to a particular condition when they have had repeated previous exposure to that condition, even when motor priming is accounted for (e.g., Yashar & Lamy, 2011).

Within attention research, studying the impact of prior trials on current behavior is increasing in popularity. Traditionally, most visual search studies have focused on either current goals (i.e., *top-down*), such as the role of search template specificity (e.g., Bravo & Farid, 2009), scene context (e.g., Castelhano & Heaven, 2011), and spatial cues (e.g., Posner, 1980), or on the physical salience of the display items (i.e., *bottom-up*), such as stimulus driven capture (e.g., Treisman & Souther, 1985) and distraction (e.g., Theeuwes, 1991). However, recent examinations of attentional control have moved away from the “top-down/bottom-up” dichotomy to also include *selection history*—the accumulated history of attentional deployments (e.g., Awh, Belopolsky, & Theeuwes, 2012; Failing & Theeuwes, 2018; Zhao, Al-Aidroos, & Turk-Browne, 2013). Selection history includes effects of reward history (e.g., Della Libera & Chelazzi, 2009), priming (e.g., Gaspelin, Gaspar, & Luck, 2019; Cochrance & Pratt, 2020), statistical regularities (e.g., Geng & Behrmann, 2005), contextual cueing (e.g., Brockmole, Castelhano, & Henderson, 2006; Chun & Jiang, 1998), and more.

While there is strong evidence that prior experience influences current performance in a way that gradually builds across trials (e.g., Maljkovic & Nakayama, 1994), the precise trial-by-trial development of these effects has not been well characterized. Such a characterization, as done here, would be valuable for understanding the nature of behavioral adaptation and its underlying neural mechanisms.

The current study used massive behavioral datasets to examine trial-by-trial changes in behavior, resulting in a data-driven quantification of the function relating current behavior to prior experience. In short, the relative frequency of prior experience with features that matched the current trial was strongly predictive of behavior on the current trial. This relationship held across two tasks and multiple features of trial history in a number of pre-registered analyses and independent replications, including prior exposure to features that were completely orthogonal to motor and response priming.

Experiment 1: A Simple Function Relating Prior Experience to Behavior

In the first experiment, the relationship between prior experience and behavior adaptation was quantified in a simple binary decision task on the basis of trial condition. In each trial, participants made a category judgement about a single object using a consistent motor action. The classified item was explicitly attended and directly relevant to the ultimate trial response. Given this task structure, motor priming, response priming, and reinforcement of the condition of interest (in this case, trial type) were perfectly aligned. Therefore, the dataset afforded a single predictor variable that could encompass all of these factors in which to establish the basic relationship relating prior experience to current behavior. Experiments 2 and 3 were then used to tease apart the factors.

Methods

Data were collected anonymously from users playing the publicly available mobile application, *Airport Scanner* (Kedlin Co., www.airportscannergame.com /airportscanner), as outlined in the Terms and Conditions agreed upon download and approved by the Institutional Review Board at The George Washington University. *Airport Scanner* is a game wherein players assumed the role of an airport security screener and conducted a series of tasks where they identified items that would be prohibited through airport security. These tasks included a primary visual search task where players searched simulated bags for prohibited items among allowed distractors, and a secondary object-sorting task where players categorized individual items as prohibited or allowed (See Experiment 2 for the visual search task). Data from players' search performance have been used previously for research purposes (e.g., Mitroff et al., 2015). The term "player" refers to each unique device ID as assigned when the application was downloaded onto a device. Due to the anonymity of data, it was not possible to ensure that only one person contributed to any given device ID, nor that each person contributed to only one unique device ID.

Object-Sorting Task

The object-sorting task (see Figure 1A) was a mini-game played upon successful completion of a visual search level within the *R&D Lab* component of *Airport Scanner*. Data were assessed for gameplay between 2016 and 2018, wherein 54,138 players attempted at least one session of the object-sorting task (range: 1-308 sessions, mean: 3.87, SD: 7.67). In the task, players had 20 seconds to make a series of binary category decisions, sorting up to 22 items as prohibited or allowed through airport security. Both speed and accuracy were reinforced through a point system (100 points for each correctly classified item in 20 seconds). Out of all possible players, data were included for 50,819 players who completed a minimum of ten trials in their first session.

The items were introduced earlier through visual search gameplay in the *R&D Lab* level of the game as items that were prohibited or allowed through an airport security checkpoint and were also reviewable in a logbook. Each item appeared in the center of the screen, and players were to touch and swipe the object to the top of the screen to identify it as prohibited or to the bottom of the screen to identify it as allowed, before proceeding to the next item. In the first level of the task, there were 22 possible prohibited items and 105 possible allowed items. Players received visual feedback at every trial and could also receive auditory feedback if the volume on their device was turned on. No information was provided to the players about the possible proportions of prohibited and allowed items, but 0-100% of trials could contain a prohibited item.

The touch-and-swipe response method allowed response times to be separated into two components: 1) the amount of time to initiate the response, and 2) the amount of time to swipe to the appropriate end of the screen. The latter was determined to be the more meaningful measure of decision (Kramer, Cox, Yu, Kravitz, & Mitroff, submitted; Kramer, Kravitz, & Mitroff, 2018) and thus served as the reported response time measure.

Data Analysis

Performance on each trial was evaluated as a function of the prior exposure to the current trial condition (i.e., prohibited or allowed item), across the first ten trials of the players' first session. Specifically, the influence of the *strength* and *amount of exposure* were evaluated. *Strength of exposure* was defined as the proportion of prior trials consistent with the current trial condition, while *amount of exposure* was simply the number of preceding trials. The joint effect of *strength* and *amount* was represented as a binomial z-score (Pearson, 1900). Data points where 100% of the prior trials were of the same trial type (e.g., all prohibited or all allowed) were excluded, as they resulted in a standard error of zero for the z-score calculation. All reported relationships between performance and prior exposure (z-score) were tested using simple linear regression. All analyses had a minimum of 100 trials per data point; at each qualifying z-score, data from 100 players were randomly selected (this was repeated 100 times and results were averaged across replications) to account for differences in trial count across z-scores (i.e., the z-scores closest to zero had many more contributing trials than the tails of the distribution).

As a control analysis, the same z-score calculation was performed, but prior history was randomly permuted across participants such that any given players' current performance was to be predicted by another randomly selected (without replacement) players' trial exposure. Everything else was held the same, and relationships between performance and random prior exposure (z-score) were tested using simple linear regression. The strength of the linear relationship, as compared to the randomized relationship from the control analysis, were compared using a Fisher's transformation and z-test.

Results

Overall, accuracy was high for both prohibited (Mean=89.96%, SD=17.82) and allowed (Mean=88.36%, SD=17.71) items. The nature of trial-by-trial behavioral adaptation was investigated across the first ten trials. Specifically, performance was evaluated at each trial as a function of the degree to which prior experience was consistent with a prohibited item occurring. First, the greater the *strength* of evidence for a particular trial condition, the better the performance on that type of trial. For example, accuracy on a prohibited item on Trial 4 was greater when two out of three (~66.7) of the prior trials had contained a prohibited item than after one out of three (~33.3%, in pink in Figure 1B) had ($t(19{,}710)=3.77$, $p=0.0002$). Second, even when holding the strength constant, the greater the *amount* of evidence, the greater the impact on behavior. For example, when strength of evidence is held constant at 66.6% of prior trials being prohibited, the impact of prior evidence on prohibited accuracy was larger on Trial 10 (six out of nine prior prohibited items) than Trial 4 (two out of three prior prohibited items) even though the same proportion of preceding trials had been prohibited ($t(11{,}551)=6.26$, $p=3.91*10^{-10}$).

While both the strength and amount of exposure to a trial condition had significant impacts on behavior, it is possible, and important, to consider these elements jointly. There are a number of standard statistical metrics that provide a means to do so, and, for the sake of simplicity, one is presented here—the binomial z-test (see

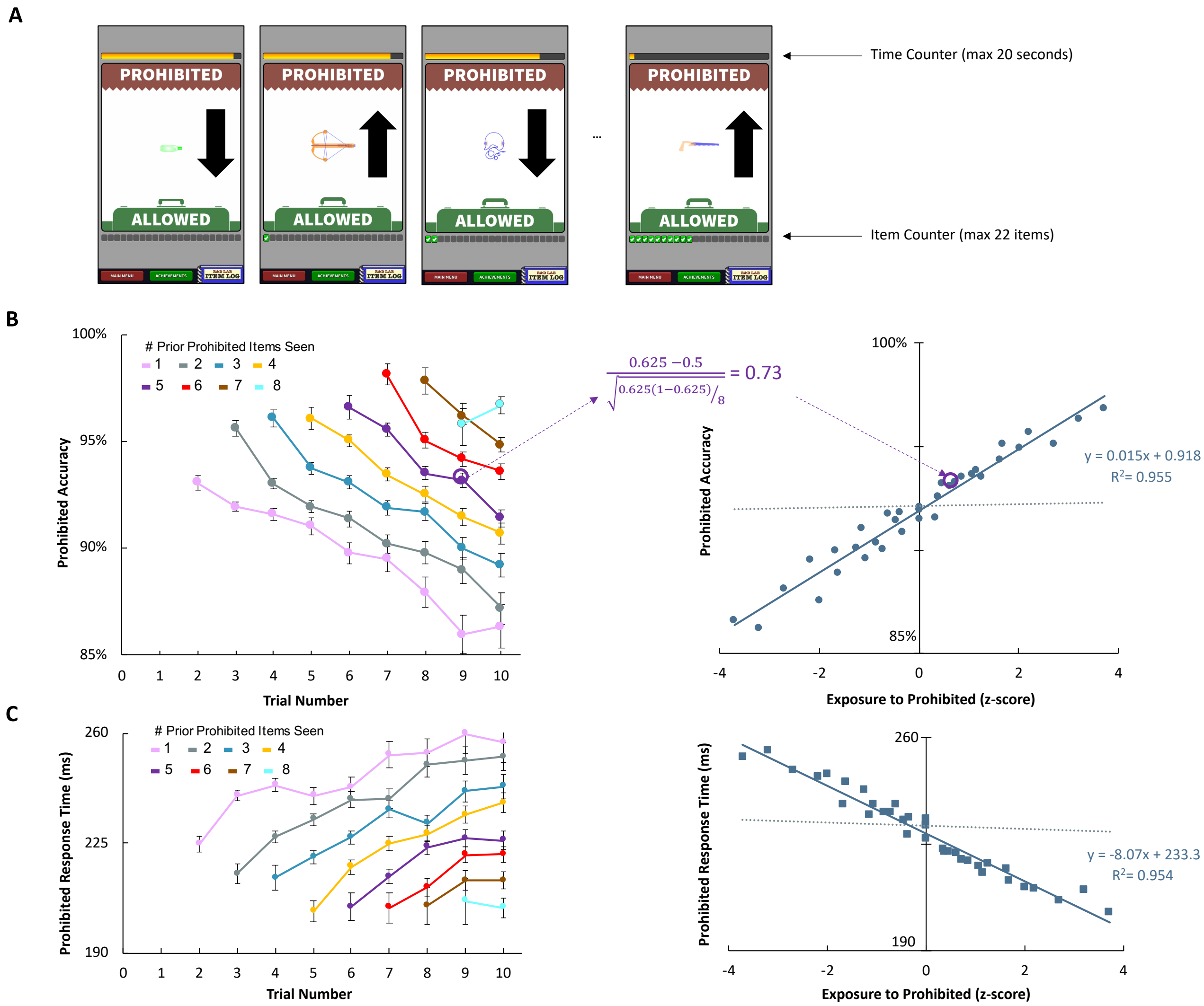


Figure 1. A) Depiction of object-sorting task. Black arrows are for demonstration purposes and were not included in the actual displays. **B)** Accuracy for prohibited items (correct classification rate) for current trial number as a function of the number of prohibited items seen prior to that trial. Each player contributed to a single data point (i.e., one possible prior prohibited item condition) for each trial (left). Average prohibited accuracy as a function of the calculated binomial z-score for each point from b; each point was transformed as a measure of the extent of exposure to that trial condition (binomial z-test equation—one example transformation highlighted in purple; right). **C)** Prohibited response time (time to correctly classify item; in ms) for current trial number as a function of the number of prohibited items seen prior to that trial (left). Prohibited response time as a function of the calculated z-score (right). Error bars are 1 standard error of the mean and lines of best fit are linear regressions. Gray dotted lined are the linear regression from the control analysis.

Supplemental Material for other metrics), an equation derived from naturally occurring statistics that is frequently used to determine if some sample proportion (*p*), referred to here as strength of evidence, derived over a certain amount of evidence (n), deviates from a known population proportion (μ). Here, μ was 0.5 as there were two trial types that occur equally often:

$$z = \frac{p - \mu}{\sqrt{\frac{p\,(1-p)}{n}}}$$

Participants were both faster and more accurate when the exposure across prior trials was more consistent with the current condition. Accuracy for prohibited items was almost perfectly predicted by the binomial z-scores (Figure 1B; R^2=0.955, p=1.63*10^{-24}), while the control analysis produced a significantly smaller (Fisher's Z: z=8.35, p<1*10^{-15}) and insignificant relationship (R^2=0.031, p>0.3). The binomial z-score also predicted accuracy on allowed items (R^2=0.926, p=8.73*10^{-21}; Control: R^2=0.0015, p>0.8; Fisher's Z: z=7.87, p=1.77*10^{-15}) which represents a replication of the effect in an independent set of trials. Further, a strong relationship was also found for response time (Figure 1D & 1E) for both prohibited trials (R^2=0.9454 p=2.72*10^{-24}; Control: R^2=0.045, p>0.2; Fisher's Z: z=8.15, p=2.22*10^{-16}) and allowed trials (R^2=0.912, p=1.58*10^{-19}; Control: R^2=0.055, p>0.15; Fisher's Z: z=6.69, p=1.13*10^{-11}). The magnitude of the effect was massive; for example, by the end of the studied period (Trial 10), average prohibited accuracy varied by over ~13% from 85% to 98% simply as a function of prior exposure.

Discussion

In this first experiment, the relationship between prior experience and current behavior was found to be precise and robust, mirroring a common statistical metric of evidence (i.e., the binomial z-test), and significantly different from a control analysis using a random permutation. However, the simplicity of the task was both a feature and a limitation. On the one hand, since there were only two possible decision outcomes and they were tied to consistent motor actions (i.e., always swipe in the same direction for one response type), there was perfect agreement between the motor priming, response priming, and reinforcement of the trial condition of interest (prohibited or allowed). All three of these factors were reinforced by experience and were captured well by the binomial z-test and other basic statistical metrics (see Supplemental Material). On the other hand, the simplicity of the task did not allow for separating out the contribution of each factor. The next two experiments further explored whether the same highly significant function held in a more complex task to 1) show the domain-generality of the effect and 2) test features that were orthogonal to motor priming (Experiment 2) and response priming (Experiment 3).

Experiment 2: Testing Generalization Across Tasks

Experiment 2 looked to replicate the data-driven analysis of Experiment 1 in a visual search task, to show that the same precise, statistical function held in a more complex task. Furthermore, the more complex motor action required of the visual search task reduced the strong tie between motor priming and reinforcement of the trial condition of interest that was seen in Experiment 1; thus, Experiment 2 provided initial insights into understanding the trial-by-trial reinforcement of cognitive events distinct from the reinforcement of purely motor events.

Methods

Data were collected from the same mobile application, *Airport Scanner*. The metrics used to define the relationship between prior exposure and current behavior were the same as Experiment 1, but Experiment 2 focused on the visual search task.

Visual Search Task

The primary task in the *Airport Scanner* game was a visual search task where players look for prohibited (target) items among allowed (distractor) items (see Figure 2A), all items were reviewable in a logbook. In this task, players progressed through a series of "airports" each containing a series of levels. Data were analyzed from players who completed the first visual search level after training (i.e., the first level in the first non-training airport, "*Honolulu*"). It was possible that some of these players may have also contributed data to the object-sorting task from Experiment 1.

The visual search level analyzed here consisted of 24 trials total. Players searched for prohibited items among allowed items in simulated x-rays of baggage moving across a conveyor belt (in the level analyzed, there could be zero to 2 targets, among zero to 14 distractors). Players indicated the presence of a target by tapping on the item in the bag with their finger. If no target was present, players cleared the bag by swiping it to the right, or passively allowing it to continue along the conveyor belt (by not touching the screen). On each trial, participants could manipulate the bag's progression across the screen by swiping the bag to speed the conveyor belt and/or tapping and holding the bag to pause the conveyor belt. Players received visual feedback at every trial and could also receive auditory feedback if the volume on their device was turned on. There was a 50% chance of a target appearing on any given trial. Both accuracy and response time were emphasized and contributed to points scored. All players included in the analyses completed the level on their first attempt, without using any in-game upgrades, and did not see any multiple target trials (i.e., they only experienced target absent or single target trials). Accuracy and response time were evaluated as a function of the evidence accumulated across each of the first ten trials as described in Experiment 1.

Data Analysis

An analogous analysis to Experiment 1 was conducted to determine the effect of trial history on behavior. Performance on the current trial was evaluated as a function of the exposure to the current trial condition (target present or target absent). The same z-score calculation from Experiment 1 was performed, and all reported relationships between performance and prior exposure (z-score) were tested using simple linear regression. All regressions were also compared to the same control analysis used in Experiment 1 using Fisher's transformations and z-tests. Specifically, the control regressions involved randomly permuting trial history across players (such that any given players performance was predicted based on a randomly selected player's trial history).

In the initial analysis, data from 1,000,000 players were included. This sample size was selected based on the available data and the desire to obtain as precise a quantification as possible of the relationship between prior exposure and current performance. The large sample size enabled an estimate for nearly every possible combination of preceding trials with at least 100 instances. Note that performance on Trial 10 for the specific instance when exactly eight of the nine prior trials were target-present was an outlier on three out of four outcome measures (hit rate, target present response time, and correct rejection rate) as measured by being more than three standard deviations from the mean, and thus was excluded from all analyses. As it was the only data value that produced outlying data, and did so on three of the four outcomes, it is likely there was a coding irregularity in the *Airport Scanner* platform for this particular case.

Pre-Registered Replications

Given the amount of data available from the full *Airport Scanner* dataset, it was possible to replicate the results in independent datasets using the same visual search parameters. Data were analyzed from an additional 1,862,369 players who completed the first visual search level of *Airport Scanner* after training between 2015 and 2017, and who did not use any in-game upgrades or see any multiple target trials in the first ten trials. The data were split into two groups of 931,184 and 931,185 players, to conduct two independent, pre-registered replications. These same subsets of data were then used to perform a pre-registered control analysis using the same random permutation as Experiment 1. More details can be found on the Open Science Framework registration (osf.io/pj64e).

Additionally, these 1,862,369 players were used to conduct a pre-registered bootstrapping analysis to characterize the distribution of the effect over 10,000 replications of 1,000,000 randomly selected players. The relationship between prior evidence and performance (accuracy and response time) was calculated for each replication, and the distribution of R^2 values is reported below. More details for this can also be found on the Open Science Framework registration (osf.io/c93n8), along with analysis codes (osf.io/wteq4).

Results

Accuracy was high for both target present (Mean=95.37%, SD=6.72) and target absent (Mean=88.14%, SD=12.03) trials. Players were both faster and more accurate when prior experience (i.e., strength and amount jointly represented as a binomial z-score) was more consistent with the current trial condition. Average hit rate for target present trials was strongly predicted by the binomial z-scores (R^2=0.814, p=1.38*10^{-13}; Figure 2B, left). The inverse relationship occurred for correct rejection rate (percentage of target absent bags that were correctly cleared) on target absent trials (R^2=0.836, p=1.69*10^{-14}; Figure 2B, right). Further, strong relationships were found for average response time in both target present trials (time in milliseconds to correctly tap on the target item; R^2=0.712, p=1.94*10^{-10}; Figure 2C, left) and target absent trials (time to correctly “clear” the bag as not containing any targets; R^2=0.814, p=1.35*10^{-13}; Figure 2C, right). These analyses demonstrated the strong and systematic adaptation of behavior to context and its tight relationship to the binomial z-score, and that the same effect from Experiment 1 was also shown in a more complex task. The target present and target absent analyses represented independent sets of analyses demonstrating the same robust relationships.

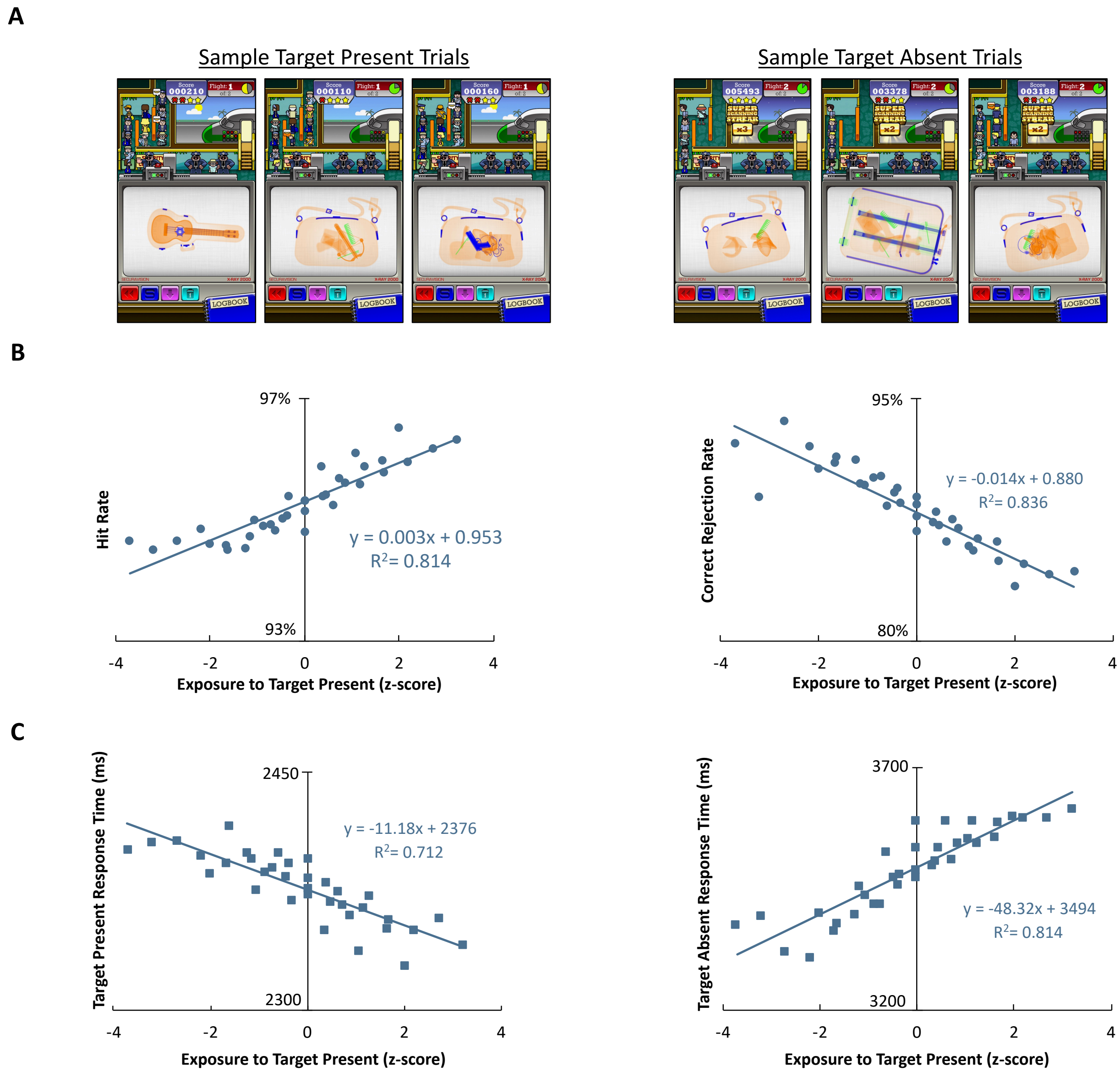


Figure 2. A) Depiction of visual search trials from Honolulu airport of Airport Scanner applications. Bags could be target present (left) or target absent (right) and varied in difficulty by a number of factors including item saliency, distractor number, and clutter. **B)** Average accuracy as a function of the extent of prior exposure to target present trials, calculated as a binomial z-score, for target present trials (hit rate, left) and target absent trials (correct rejection rate, right). **C)** Average response time (ms) as a function of the extent of prior exposure to target present trials, calculated as a binomial z-score, for target present trials (left) and target absent trials (right).

Pre-Registered Replications

All results were replicated in the two independent samples (N_1=931,184; N_2=931,185; see Figure 3). Significant linear relationships in the expected directions were found for hit rate (Replication #1: R^2=0.844, p=7.18*10^{-15}; Replication #2:

R^2=0.868, p=4.34*10^{-16}), correct rejection rate (Replication #1: R^2=0.928, p=2.16*10^{-20}; Replication #2: R^2=0.910, p=7.66*10^{-19}), target present response time (Replication #1: R^2=0.806, p=2.79*10^{-13}; Replication #2: R^2=0.886, p=1.19*10^{-16}), and target absent response time (Replication #1: R^2=0.691, p=6.23*10^{-10}; Replication #2: R^2=0.755, p=1.31*10^{-11}).

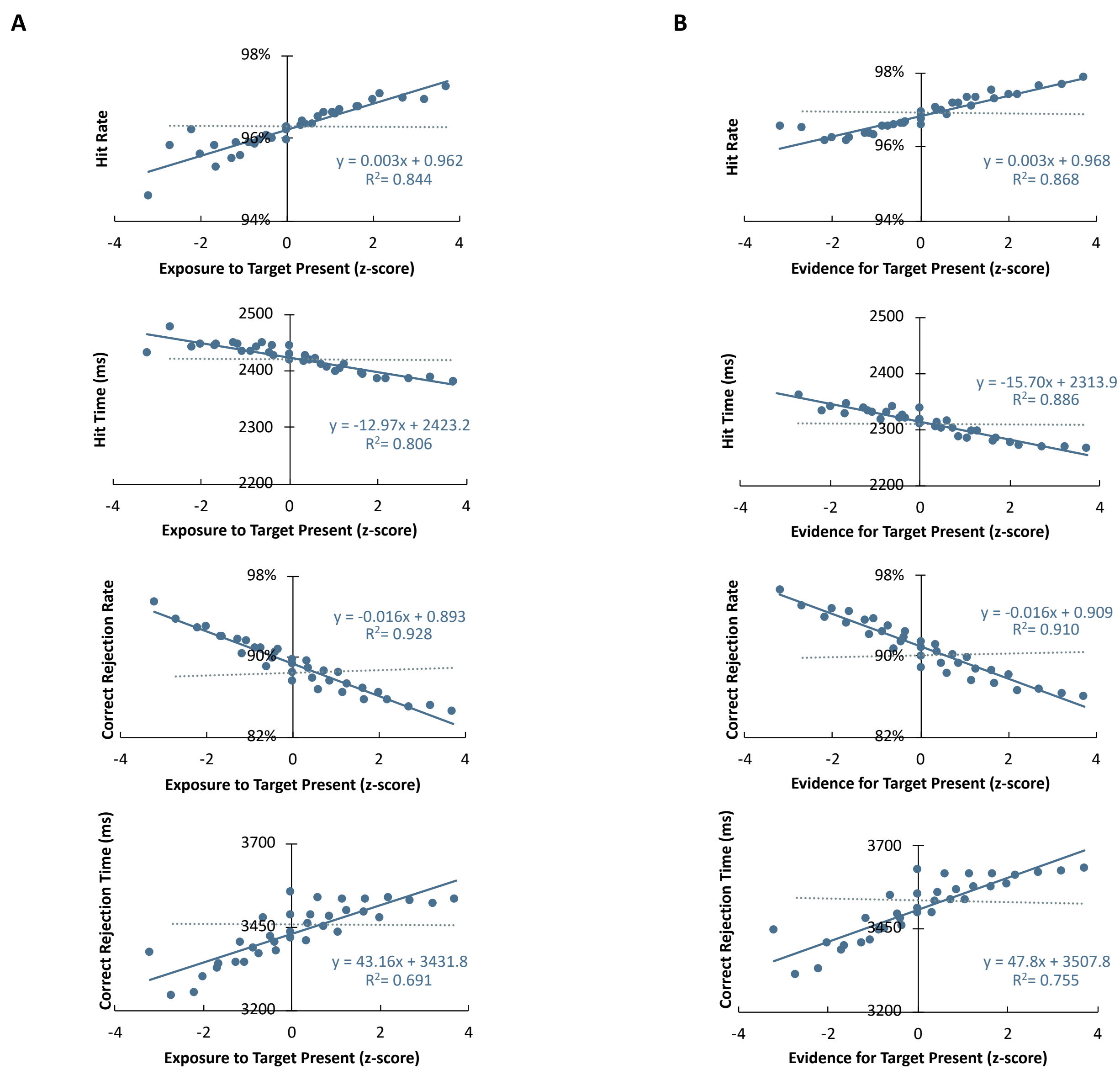


Figure 3. Results from Replication #1 (**A**) and Replication #2 (**B**). Control regression lines of best fit shown in dotted lines.

As predicted, control analyses did not show significant relationships between random prior exposure and current performance (all R^2 values <0.09, all p-values >0.09), and those relationships were significantly weaker than the actual relationship between prior exposure and currently performance (all z-values >4.5, all *p*-values $<1*10^{-5}$).

To more fully characterize the distribution of R^2 values that could result from any grouping of these participants, 10,000 random samples of 1,000,000 players from the combined replication dataset (n=1,862,369) were generated. These samples revealed a consistent and strong relationship (R^2) between prior exposure (z-score) and all metrics of performance: hit rate (M=0.876, SD=0.049, 95% CI=[0.779, 0.973]); correct rejection rate (M=0.898, SD=0.008, 95% CI=[0.883, 0.914]); target present response time (M=0.893, SD=0.038, 95% CI=[0.819, 0.967]); and target absent response time (M=0.746, SD=0.044, 95% CI=[0.660, 0.831]).

Discussion

In Experiment 1, a strong, precise relationship was found between prior exposure to a trial condition and subsequent performance, whereby current behavior was optimized proportional to the statistical evidence for the current trial condition. Experiment 2 revealed that the same relationship existed in a more complex visual search task. This second experiment served two main purposes. First, it provided a replication of the effect in another task, coupled with additional internal pre-registered replications within the task, showing the generality and consistency of the finding. Second, the more complex motor actions in the visual search task (swiping bags across the screen and tapping bags both to manipulate conveyor belt speed as well as to respond), allowed for initial insights into teasing apart the exact mechanisms underlying the trial-by-trial accumulation of information. As discussed in the Introduction, carryover effects can be driven by priming of the motor response, response set, and/or cognitive feature of interest. The robust relationship between prior experience and current performance despite clear changes in the motor actions suggested that the effect was not entirely driven by motor reinforcement. However, the reinforced event was still directly tied to response selection (i.e., target present or target absent). Experiment 3 explored the trial-by-trial carryover in experimental components orthogonal to target present/target absent responses, which provided a direct way to isolate the reinforcement of cognitive events, above and beyond motor or response priming.

Experiment 3: Generalizing the Function for Task-Irrelevant Features

In visual search, attentional deployments to a target in prior trials (as studied in Experiment 2) are directly tied to the response (target absent or target present) and the associated motor action of that response (i.e., specific keypress responses, or, in this case, tapping vs. swiping). As such, Experiment 2's effect could have been influenced by a strong relationship between prior trial experience and priming of response selection (and even a loose relationship between prior exposure and motor priming). The third experiment addressed whether the occurrence of features that were orthogonal to the presence of a target, and therefore could be isolated from motor and response priming, could generate the same direct relationship with subsequent performance that was seen across the first two experiments.

Methods

Data were analyzed from the same visual search task from Experiment 2. Given the reduced frequency of the events being analyzed in the current experiment, a larger sample was obtained; the exact sample size (1,554,725 players) was determined by the amount of data available to the research team at time of data processing). All other parameters and inclusion criteria remained the same as Experiments 1 and 2. The two analyses conducted evaluated current performance based on a players' prior exposure to: 1) a salient distractor that could be present in some trials and 2) the "bag type" on each trial–a non-salient background feature. Importantly, neither the presence of the distractor nor the bag type was indicative of whether a target would be present; therefore, there was no explicit reason for players to track information regarding these features, nor was the occurrence of distractors or bag type tied in any way to motor or response priming. As such, if these analyses were to reveal the same evidence accumulation function relating current performance to the occurrence of either factor (the distractor or bag type), then it would provide strong evidence for feature-level reinforcement in the absence of motor and response priming.

Data Analysis and Results

Analysis 1: Salient Distractor

Data Analysis. The specific distractor selected for the analysis was the "headphones." In the early level of *Airport* Scanner used for the current analyses, most of the distractor items were light orange or light green with varying levels of translucency, in contrast with the majority of targets which were dark blue and largely opaque. The headphones were selected for being one of the few distractors that were also dark blue and opaque (see Figure 4A). The presence of the headphones distractor did not indicate the presence or absence of a target, but was likely to draw attention due to its relative salience. The purpose of this analysis was to determine if the same evidence accumulation function seen in Experiments 1 and 2 also described the relationship between players' experience with ignoring and/or rejecting a salient distractor across previous trials and subsequent performance on both target present and target absent trials that also contain that salient distractor (see Mruczek & Sheinberg, 2005).

First, performance on the current trial was evaluated as a function of the proportion of prior trials that had contained headphones, represented as a z-score (where μ was the average proportion of trials containing headphones by the end of the first ten trials across participants). Performance as a function of prior exposure was calculated across the first ten trials, with each combination of prior exposure having at least 400 instances contributing to the data point (similar to the prior experiments, data from 400 players were randomly selected at each qualifying z-score, which was repeated 400 times with results averaged across replications to account for differences in trial count across z-scores). As in Experiments 1 and 2, relationships between performance and prior exposure (z-score) were tested using simple linear regression, and compared to the pre-registered control analysis (osf.io/wteq4).

Results. Participants were both more accurate and faster on trials containing headphones if they had experienced more trials containing headphones prior to that point (Figure 4B). In target present trials, strong linear relationships were found between z-score for exposure to headphones and hit rate (R^2=0.335, p=2.15*10^{-4}) and target hit

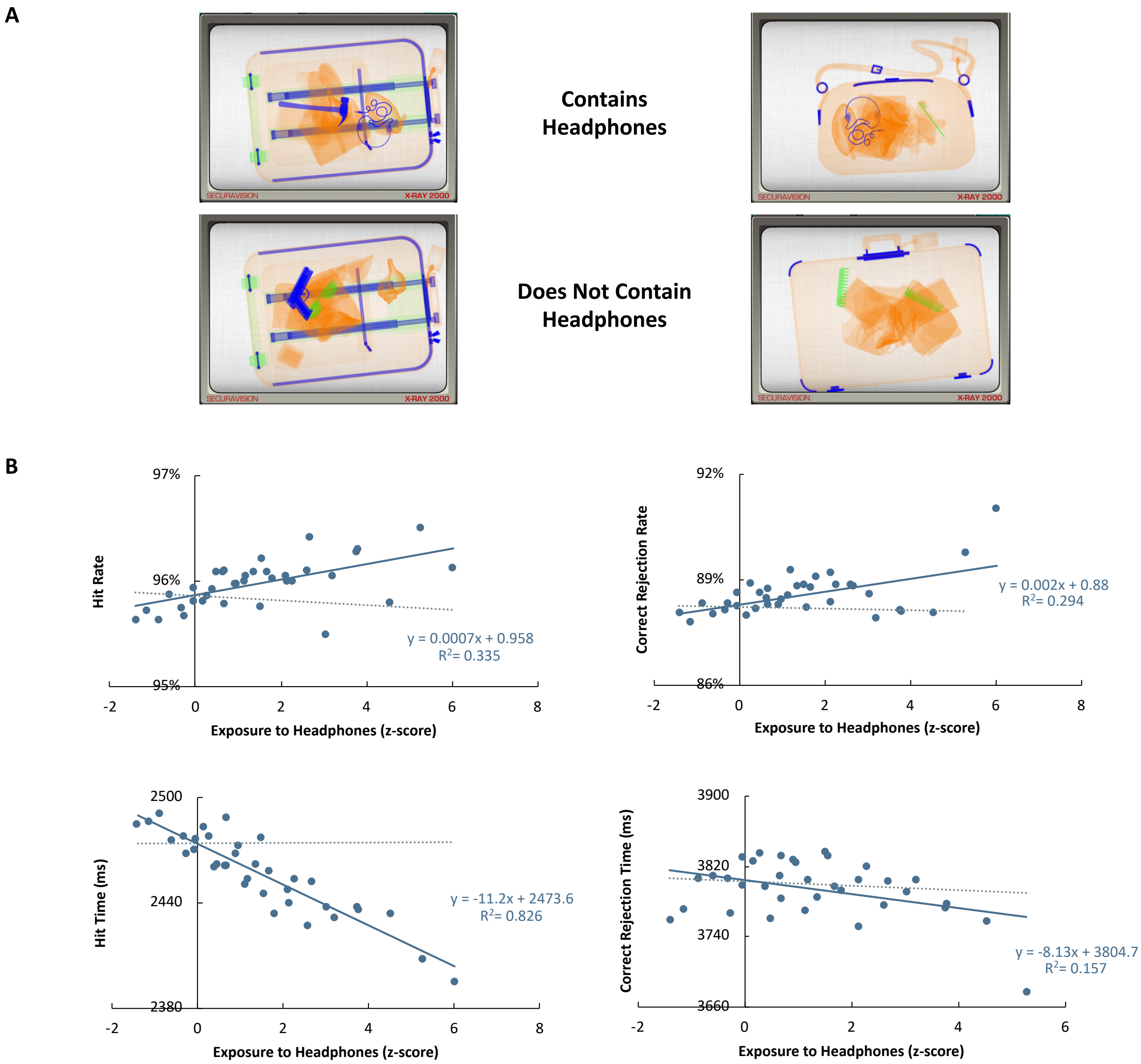


Figure 4. A) Exemplars of target present (left) and target absent (right) bags that contain headphones (top) and that do not contain headphones (bottom). **B)** Performance on bags containing headphones as a function of prior exposure to bags containing headphones, measured as a z-score. Control regression lines of best fit shown in dotted lines.

time (R^2=0.826, p=1.88*10^{-14}). Similarly, in target absent trials, significant linear relationships were found between z-score for exposure to headphones and correct rejection rate (R^2=0.294, p=6.25*10^{-4}) and correct rejection response time (R^2=0.157, p=0.019). As predicted, the control analysis for all outcome variables did not show significant relationships between random history of exposure to headphones and current performance on headphones (all R^2 values <0.04, all p-values >0.26). The results of the control analyses were also significantly different from the actual relationship between trial history and current performance for three of the four outcome variables (z's >1.89, p <0.03), but not correct rejection response time (z=1.26, p=0.10).

Analysis 2. Bag Type

Data Analysis. In the level of visual search examined, there were six possible background bag types on any given trial. Two of the six bag types–a "fish" and "ukulele"–were unique to the level ("Honolulu") and could only contain zero or one target (no distractors); as such, and given their unique nature, they were excluded from this analysis. The remaining four bag types– "*carry-on*," "*duffle*," "*purse*," and "*briefcase*" (seen in Figure 5A)–provided visual noise in the background, but had no predictive value for target presence. This analysis provided a further test of the notion that players were influenced even by the occurrence of features that were unrelated to target presence, and the visual noise provided by the different bag types were arguably even less important to attend to than a salient distractor item. It was hypothesized that, despite bag type lacking any predictive value of response, the same, evidence accumulation function would be seen yet again in which the greater the prior exposure to a particular bag type, the better performance would be on a subsequent trial involving that bag type (see Richards & Reicher, 1978).

Performance on the current trial was evaluated as a function of the players exposure to each of the four major bag types (carry-on, duffle, purse, and briefcase) across previous trials, represented as a z-score (μ was the average proportion of trials containing that bag type by the end of the first ten trials across participants) using the same technique and minimum trial counts as for headphones. Specifically, performance was measured as time to correctly clear a target absent bag, and was evaluated for each bag type. For example, prior exposure to briefcase bags was related to performance on a subsequent target absent trial that involved a briefcase bag. For the carry-on bag type, performance on Trials 9 and 10 were outliers, and thus were removed from analyses (subsequent exploration into this revealed that performance on these trials was consistently an outlier for carry-on bags across outcome measures including both accuracy and response time, and thus it was deduced that there was likely a coding irregularity in the game). However, since Trials 9 and 10 were not outliers for the remaining three bag types (duffle, purse, and briefcase), the data points were only removed from analysis for the carry-on bag type.

Again, all reported relationships between performance and prior exposure (z-score) were tested using simple linear regression. The same control analysis from Experiments 1 and 2 was also used here (pre-registered on OSF: osf.io/wteq4).

Results. There was a strong linear relationship between z-score of prior trials containing a particular bag type and time to correctly deem a bag as “target absent” on a subsequent trial of the same bag type (Figure 5B). The more exposure to briefcase bags, the faster the performance on a subsequent briefcase bag (R^2=0.366, p=8.28*10^{-4}). This was replicated for carry-on bags (R^2=0.704, p=2.53*10^{-5}), purses (R^2=0.489, p=4.92*10^{-5}), and duffle bags (R^2=0.246, p=8.52*10^{-3}).

The control analysis for all outcome variables did not show a significant relationship between random history of exposure to bag type and current performance on that bag type (all R^2 values <0.02, all p-values >0.4). The results of the control analyses were also significantly different from the actual relationship between trial

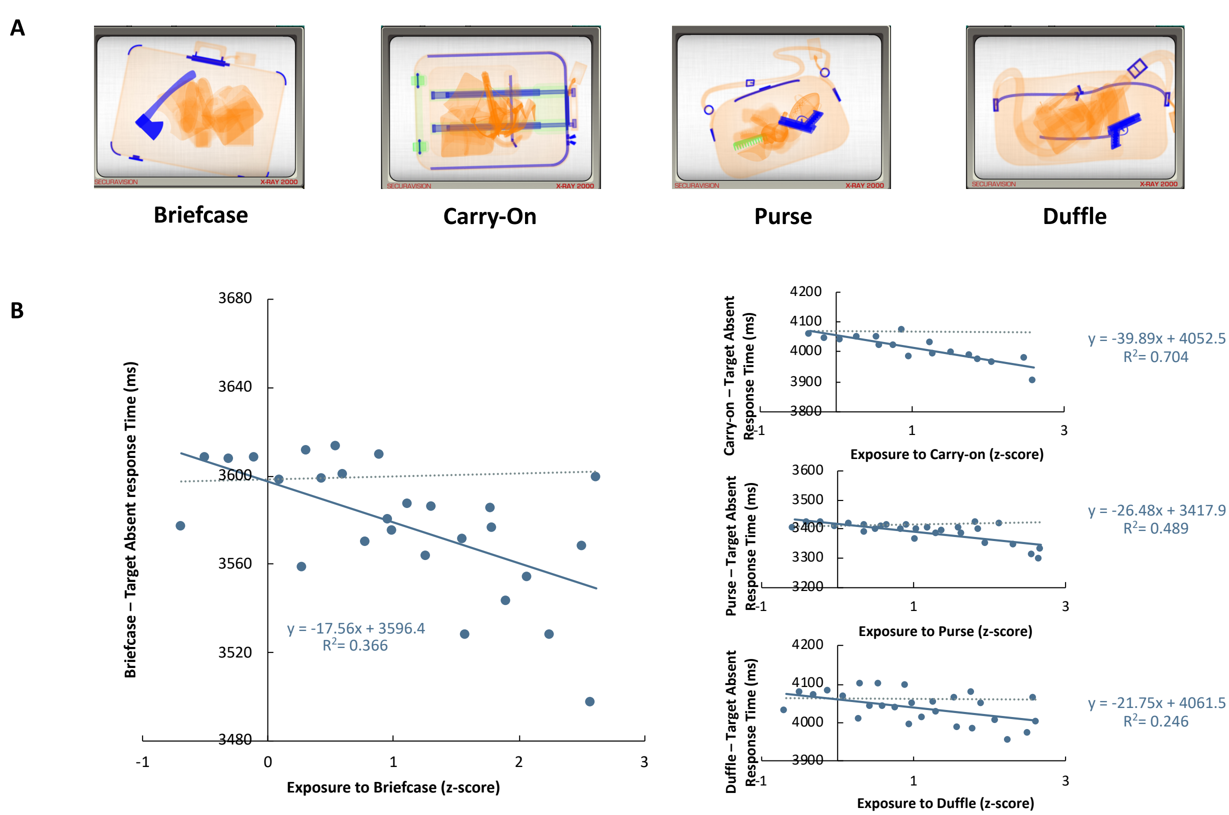


Figure 5. A) Example images of the 4 major bag types, briefcase, carry-on, purse, and duffle (all shown here as target present trials, from left to right, bags contain an axe, a crossbow, a pistol and a pistol). **B)** Target absent response time on briefcases (left) as a function of prior exposure to trials containing briefcases, measured as a z-score. The same relationship is also shown for carry-ons (right, top), purses (right, middle), and duffles (right, bottom).

history and current performance for all bag types (all Fisher's Z: z -values >1.85, p <0.032).

Discussion

The first two experiments both revealed a strong, precise relationship between prior exposure to a trial condition and current performance, wherein current behavior was optimized proportional to the statistical evidence for the current trial condition. This third experiment showed the same relationship in features that were unrelated to trial response; current performance was directly related to the statistical evidence accumulated with regards to both the occurrence of a salient distractor and the occurrence of non-salient background "bag type," despite these features having no relation or predictive value to the presence of a target. This result served to clearly isolate the cognitive effects of prior trial history from the effects of motor and response priming. Targets were equally likely to occur whether or not headphones were present, and were equally likely to occur in all bag types. Thus, the findings provided clear evidence that the trial-by-trial reinforcement characterized here must involve reinforcement of cognitive (i.e., attentional and perceptual) aspects of the task (above and beyond motor or response priming).

Furthermore, a feature did not have to be salient, explicitly task-relevant, or even likely to be attended to in order for the effect to occur. Players were more efficient in visual search trials that shared even non-salient distracting information (i.e., bag type) with prior trials, suggesting that players improved at rejecting distractors with increased exposure in a manner that is well-predicted by the same evidence accumulation function from the previous experiments. This reinforcement occurred even with features that did not need to be directly attended for players to complete the task of determining target presence.

General Discussion

The current study provided a data-driven characterization of the trial-by-trial adaptation of behavior based on prior experience. These changes were found to be 1) precise and robust, largely mirroring common metrics of statistical evidence; 2) evident across two distinct tasks and multiple features, consistent with domain generality; and 3) evident even in features that were not predictive of trial condition or ultimate response.

The current findings are relevant for a number of realms, including behavior and neural experimentation, and various practical issues. For example, they bear on the debate of whether explicit attention is required for statistical learning (e.g., (Musz, Weber, & Thompson-Schill, 2014; Turk-Browne, Jungé, & Scholl, 2005), suggesting that, at least in the absence of active suppression, statistical learning can occur for even non-salient and likely unattended items (see also Zhao, Al-Aidroos, & Turk-Browne, 2013).

Potential relationship to neural mechanisms

The systematic and domain-general (shown in two tasks and across multiple features of varying levels of task relevance) function revealed here is consistent with proposals that the mechanism underlying reinforcement-based behavioral change is distributed neuronal plasticity within local cortical circuits (e.g., Reber, 2013; Goujon, Didierjean & Thorpe, 2015). Given that the diverse processes (motor priming, response selection, and cognitive components, including decision-making, attention and perception) that this study demonstrated are well described by a single evidence accumulation function, a single ubiquitous mechanism would provide the most parsimonious explanation. One commonality between all of those circuits that could explain the evidence accumulation function is simple Hebbian learning (Hebb, 1949) supported by a number of short- and long-term mechanisms of synaptic plasticity (e.g., Kelleher, Govindarajan, & Tonegawa, 2004; Mongillo, Barak, & Tsodyks, 2008).

A mechanism supported by any form of synaptic plasticity is likely to be automatic and unsupervised, constantly aggregating information across every presentation of every feature (Goujon, Didierjean, & Thorpe, 2015). This pattern was supported by the findings of the current study, such that even features that were not likely to be explicitly attended (such as bag type) were reinforced in the same direct (i.e., consistent with statistical metrics) manner as explicitly relevant features, such as trial condition. As such, the suggested automaticity of the effect relates to debates of what is meant by the term “task-relevant.” The findings of the current study suggested that, at least during early experience, humans accumulate information about every feature, regardless of its direct relevance to the response. While not directly explored in the current study, it is likely that features that are more closely tied to the response decision would be weighted more heavily, and possible that these weightings could change with additional experience (e.g., Masquelier, Guyonneau, & Thorpe, 2009). In fact, the pattern of change in feature weightings with task experience could be a continuous metric of which features a participant has determined to be task-relevant (and is a possible explanation for the lower variance explained by the salient distractor and bag type, as compared to trial condition).

Experimental implications

Randomizing and counterbalancing trial order—a common practice to account for experimental carryover effects—removes systematic effects of prior experience by evenly distributing the effects across participants, but leaves in place residual noise (and is not a plausible solution for individual difference studies wherein only subject-level comparisons are made and results are not averaged across participants). However, with the characterization of how behavior is influenced by trial history demonstrated in the current study, it might be possible to fit an individual's trial sequence to the binomial z-score kernel to actually *remove* the effect. Furthermore, these findings suggested that not only should the overall order of trial condition be accounted for in these kernels, but that *every* feature could have a systematic effect on behavior and thus as many features should be included in kernels as possible. This practice would reduce the impact of trial sequence and could potentially improve inferential power, especially for individual difference studies, and studies with a small number of trials and/or participants (e.g., developmental studies).

Practical implications

Performance in professions involving visual search will also be subject to these trial sequence influences. Given that most real-world searches are not statistically dependent on each other, the impact of trial sequence is likely to result in behavioral fallacies. For example, airport security screeners and radiologists look at image after image with targets rarely present (e.g., cancer is present in ~0.5% of routine mammograms; Consortium, 2009), but any given search is just as likely as the last to contain a target. Nonetheless, when a screener completes many searches that do not contain targets, they are likely to accumulate information that targets are rare, which can negatively influence their ability to identify a target in the next image (e.g., Wolfe, Horowitz, & Kenner, 2005). Furthermore, the dangers of prior experience are not limited only to the history of target presence; other aspects of prior searches (e.g., presence of salient distractors) can also influence the ability of a professional searcher to find a target. However, with the characterization of behavior revealed in this study, it might be possible to leverage this improved understanding of how behavior is impacted by prior exposure to strategically alter experience (e.g., with breaks and/or searches known to contain targets or problematic distractors; Wolfe et al., 2007) to bolster performance.

Conclusion

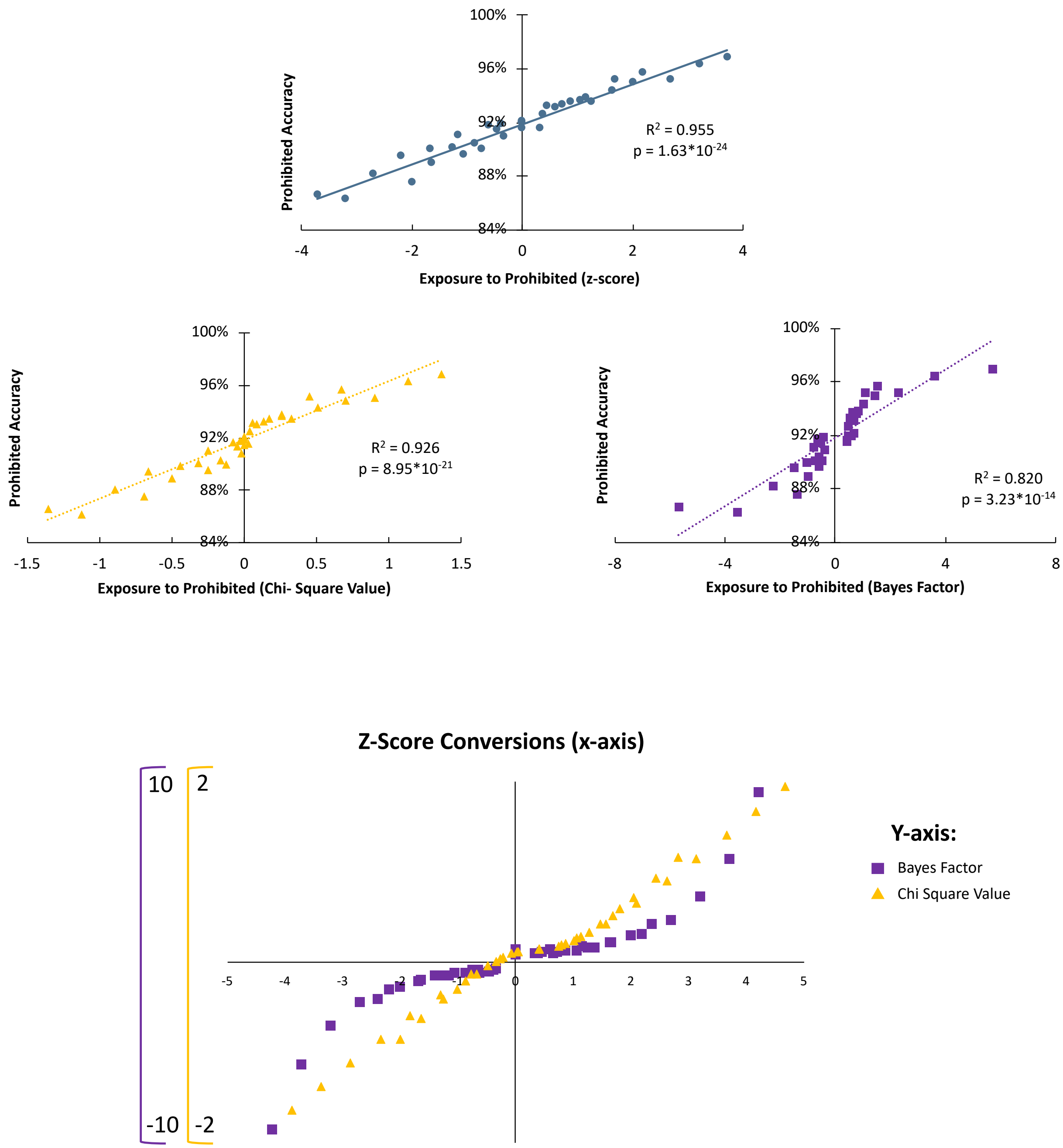
In summary, the direct, systematic relationship between prior evidence and current behavior is intuitive, but was previously not well characterized. The delineation of a precise, replicable, generalizable, and stable function relating evidence to behavioral change is important for theoretical, experimental, and pragmatic advances.

Code and Data Availability

All analysis code can be found within the OSF (osf.io/pj64e). The data that support the findings of this study are owned by Kedlin Company, and were made available to the authors for research purposes. Restrictions apply to the availability of these data and all requests must be made to Kedlin Company through the authors. Upon reasonable request, the authors can assist interested parties in making the request to Kedlin Company for access to the subset of data used for the current research purposes.

Supplemental Material

The metric of statistical evidence used throughout the study was the binomial z-test, which was selected due to its simplicity and limited number of assumptions involved. However, there are a number of other available statistical metrics that could have been used to characterize prior evidence, including a Chi-square value and Bayes factor. Supplemental Figure 1 depicts the relationship between accuracy on the Object Sorting Task (Experiment 1) and prior evidence measured with each of these statistical metrics. Supplemental Table 1 provides a table of all regression results (R^2 and p-values) for the reported relationships across Experiment 1, 2, and 3 using Z-values, chi-square values, and Bayes factors as the metric of statistical evidence.



Supplemental Figure 1. Relationship between prohibited accuracy on the object-sorting task (Experiment 1) as a function of prior exposure to prohibited items is shown for three possible metrics of statistical evidence: Binomial z-score (top), Chi-Square Value (bottom left), and Bayes Factor (bottom right). Bottom-most graph depicts scaled relationship between z-score and the other statistical metrics named.

	Z-value		Chi Square Value		Bayes Factor	
	R^2	p	R^2	p	R^2	p
Experiment 1						
Object Sorting Task						
- Prohibited Accuracy	0.955	$1.63*10^{-24}$	0.926	$8.95*10^{-21}$	0.820	$3.23*10^{-14}$
- Allowed Accuracy	0.926	$8.73*10^{-21}$	0.898	$1.90*10^{-18}$	0.815	$5.70*10^{-14}$
- Prohibited RT	0.954	$2.72*10^{-24}$	0.900	$1.47*10^{-18}$	0.783	$7.98*10^{-13}$
- Allowed RT	0.912	$1.58*10^{-19}$	0.900	$1.41*10^{-18}$	0.788	$5.18*10^{-13}$
Experiment 2						
Visual Search (n=						
1,000,000)	0.814	$1.38*10^{-13}$	0.743	$2.84*10^{-11}$	0.593	$6.41*10^{-8}$
- Hit Rate	0.712	$1.94*10^{-10}$	0.650	$5.10*10^{-9}$	0.533	$6.44*10^{-7}$
- Correct Rejection	0.836	$1.69*10^{-14}$	0.764	$7.03*10^{-12}$	0.646	$6.17*10^{-9}$
- Hit Time	0.814	$1.35*10^{-13}$	0.744	$2.80*10^{-11}$	0.645	$6.32*10^{-9}$
- CR Time						
Visual Search Rep #1						
- Hit Rate	0.844	$7.18*10^{-15}$	0.802	$3.67*10^{-13}$	0.733	$5.45*10^{-11}$
- Correct Rejection	0.928	$2.16*10^{-20}$	0.884	$5.35*10^{-17}$	0.808	$2.21*10^{-13}$
- Hit Time	0.806	$2.79*10^{-13}$	0.736	$4.48*10^{-11}$	0.625	$1.62*10^{-8}$
- CR Time	0.691	$6.23*10^{-10}$	0.623	$1.75*10^{-8}$	0.546	$3.94*10^{-7}$
Visual Search Rep #2						
- Hit Rate	0.868	$4.34*10^{-16}$	0.793	$7.77*10^{-13}$	0.705	$2.94*10^{-10}$
- Correct Rejection	0.910	$7.66*10^{-19}$	0.856	$1.89*10^{-15}$	0.785	$1.54*10^{-12}$
- Hit Time	0.886	$1.19*10^{-16}$	0.836	$3.85*10^{-14}$	0.714	$3.20*10^{-10}$
- CR Time	0.755	$1.31*10^{-11}$	0.682	$1.02*10^{-9}$	0.602	$4.44*10^{-8}$
Experiment 3						
Headphones Distractor						
- Hit Rate	0.335	$2.15*10^{-4}$	0.271	0.00114	0.069	0.12 (ns)
- Correct Rejection	0.294	$6.25*10^{-4}$	0.253	0.00177	0.559	$1.62*10^{-7}$
- Hit Time	0.826	$1.88*10^{-14}$	0.797	$2.51*10^{-13}$	0.377	$6.86*10^{-5}$
- CR Time	0.157	0.0186	0.258	0.00181	0.478	$4.20*10^{-6}$
Bag Type (CR Time)						
- Briefcase	0.366	$8.28*10^{-4}$	0.439	$1.68*10^{-4}$	0.382	$5.94*10^{-4}$
- Carry-on	0.704	$2.53*10^{-5}$	0.696	$3.14*10^{-5}$	0.553	$6.25*10^{-4}$
- Purse	0.489	$4.92*10^{-5}$	0.593	$2.64*10^{-6}$	0.721	$2.12*10^{-8}$
- Duffle	0.246	0.00852	0.251	0.00781	0.082	0.15 (ns)

Supplemental Table 1. Summary of regression results for each of the analyses presented in the main text based on the calculation of statistical evidence to quantify prior exposure to a trial condition.

References

Awh, E., Belopolsky, A. V, & Theeuwes, J. (2012). Top-down versus bottom-up attentional control: a failed theoretical dichotomy. *Trends in Cognitive Sciences*, *16*(8), 437–443. https://doi.org/10.1016/J.TICS.2012.06.010

Bravo, M. J., & Farid, H. (2009). The specificity of the search template. *Journal of Vision*, *9*(1), 34–34. https://doi.org/10.1167/9.1.34

Brockmole, J. R., Castelhano, M. S., & Henderson, J. M. (2006). Contextual cueing in naturalistic scenes: Global and local contexts. *Journal of Experimental Psychology: Learning Memory and Cognition*, *32*(4), 699–706. https://doi.org/10.1037/0278-7393.32.4.699

Castelhano, M. S., & Heaven, C. (2011). Scene context influences without scene gist: Eye movements guided by spatial associations in visual search. *Psychonomic Bulletin & Review*, *18*(5), 890–896. https://doi.org/10.3758/s13423-011-0107-8

Chun, M. M., & Jiang, Y. (1998). Contextual cueing: Implicit learning and memory of visual context guides spatial attention. *Cognitive Psychology*, *36*(1), 28–71.

Consortium, B. C. S. (2009). *Cancer rate (per 1,000 examinations) and cancer detection rate (per 1,000 examinations) for 1,960,150 screening mammography examinations from 2002 to 2006 by age*.

Della Libera, C., & Chelazzi, L. (2009). Learning to attend and to ignore Is a matter of gains and losses. *Psychological Science*, *20*(6). Retrieved from https://journals.sagepub.com/doi/pdf/10.1111/j.1467-9280.2009.02360.x

Doyen, S., Klein, O., Simons, D. J., & Cleeremans, A. (2014). The other side of the mirror. *Social Congition*, *32*, 12–32. https://doi.org/10.1016/s1261-694x(11)70243-7

Failing, M., & Theeuwes, J. (2018). Selection history: How reward modulates selectivity of visual attention. *Psychonomic Bulletin & Review*, *25*(2), 514–538. https://doi.org/10.3758/s13423-017-1380-y

Farrell, P. S. E. (1999). The hysteresis effect. *Human Factors*, *41*(2), 226–240. https://doi.org/10.1518/001872099779591259

Gaspelin, N., Gaspar, J. M., & Luck, S. J. (2019). Oculomotor inhibition of salient distractors: Voluntary inhibition cannot override selection history. *Visual Cognition*, 1–20. https://doi.org/10.1080/13506285.2019.1600090

Geng, J. J., & Behrmann, M. (2005). Spatial probability as attentional cue. *Perception & Psychophysics*, *67*(7), 1252–1268. Retrieved from https://link.springer.com/content/pdf/10.3758/BF03193557.pdf

Goujon, A., Didierjean, A., & Thorpe, S. (2015). Investigating implicit statistical learning mechanisms through contextual cueing. *Trends in Cognitive Sciences*, *19*(9), 524–533. https://doi.org/10.1016/j.tics.2015.07.009

Greenwald, A. G. (1976). Within-subjects designs: To use or not to use? *Psychological Bulletin*, *83*(2), 314–320. https://doi.org/10.1037/0033-2909.83.2.314

Hebb, D. O. (1949). The organization of behavior; a neuropsycholoical theory. In *A Wiley Book in Clinical Psychology* (pp. 62–78).

Kelleher, R. J., Govindarajan, A., & Tonegawa, S. (2004). Translational regulatory mechanisms in persistent forms of synaptic plasticity. *Neuron*, *44*, 59–73.

Kramer, M. R., Cox, P. H., Yu, A. B., Kravitz, D. J., & Mitroff, S. R. (submitted). *Moving* *beyond the keypress: As technology advances, so should psychology response time measures*.

Kramer, M. R., Kravitz, D. J., & Mitroff, S. R. (2018). Get more out of your data: Breaking down response time to improve its usefulness. *Journal of Vision*, *18*(10), 1033–1033.

Maljkovic, V., & Nakayama, K. (1994). Priming of pop-out: I. Role of features. In *Memory & Cognition* (Vol. 22). Retrieved from https://link.springer.com/content/pdf/10.3758/BF03209251.pdf

Masquelier, T., Guyonneau, R., & Thorpe, S. J. (2009). Competitive STDP-based spike pattern learning. *Neural Computation*, *21*(5), 1259–1276. https://doi.org/10.1162/neco.2008.06-08-804

Mitroff, S. R., Biggs, A. T., Adamo, S. H., Dowd, E. W., Winkle, J., & Clark, K. (2015). What can 1 billion trials tell us about visual search? *Journal of Experimental Psychology: Human Perception and Performance*, *41*(1). https://doi.org/10.1037/xhp0000012

Mongillo, G., Barak, O., & Tsodyks, M. (2008). Synaptic theory of working memory. *Science*, *319*(5869), 1543–1547. https://doi.org/10.1126/science.1150769

Mruczek, R. E. B., & Sheinberg, D. L. (2005). Distractor familiarity leads to more efficient visual search for complex stimuli. *Perception & Psychophysics*, *67*(6), 1016–1031. https://doi.org/10.3758/BF03193628

Musz, E., Weber, M. J., & Thompson-Schill, S. L. (2014). Visual statistical learning is not reliably modulated by selective attention to isolated events. *Attention,* *Perception, and Psychophysics*, *77*(1), 78–96. https://doi.org/10.3758/s13414-014-0757-5

Pearson, K. (1900). On the criterion that a given system of deviations from the probable in the case of a correlated system of variables is such that it can be reasonably supposed to have arisen from random sampling. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, *50*(302), 157–175.

Posner, M. I. (1980). Orienting of attention. *Quarterly Journal of Experimental Psychology*, *32*, 3–25.

Reber, P. J. (2013). The neural basis of implicit learning and memory: A review of neuropsychological and neuroimaging research. *Neuropsychologia*, *51*(10), 2026–2042. https://doi.org/10.1016/j.neuropsychologia.2013.06.019

Richards, J. T., & Reicher, G. M. (1978). The effect of background familiarity in visual search : An analysis of underlying factors. *Perception & Psychophysics*, *23*(6), 499–505.

Schwiedrzik, C. M., & Sudmann, S. S. (2020). Pupil diameter tracks statistical structure in the environment to increase visual sensitivity. *Journal of Neuroscience*, *40*(23), 4565–4575. https://doi.org/10.1523/JNEUROSCI.0216-20.2020

Smith, J. L., Johnstone, S. J., & Barry, R. J. (2008). Movement-related potentials in the Go/NoGo task: The P3 reflects both cognitive and motor inhibition. *Clinical Neurophysiology*, *119*(3), 704–714. https://doi.org/10.1016/j.clinph.2007.11.042

Theeuwes, J. (1991). Cross-dimensional perceptual selectivity. *Perception & Psychophysics*, *50*(2), 184–193. Retrieved from https://link.springer.com/content/pdf/10.3758/BF03212219.pdf

Tipper, S. P., & Driver, J. (1988). Negative priming between pictures and words in a selective attention task: Evidence for semantic processing of ignored stimuli. *Memory & Cognition*, *16*(1), 64–70. https://doi.org/10.3758/BF03197746

Tourangeau, R., Rasinski, K. A., Bradburn, N., & Andrade, R. D. (1989). Carryover effects in attitude surveys. *Public Opinion Quarterly*, *53*(4), 595–524. https://doi.org/10.1086/269169

Treisman, A., & Souther, J. (1985). General processing of separable features. *Journal of Experimental Psychology*, *114*(3), 285–310. https://doi.org/10.1037/0096-3445.114.3.285

Turk-Browne, N. B., Jungé, J. A., & Scholl, B. J. (2005). The automaticity of visual statistical learning. *Journal of Experimental Psychology: General General*, *134*(4), 552–564. https://doi.org/10.1037/0096-3445.134.4.552

Wolfe, J. M., Horowitz, T. S., & Kenner, N. M. (2005). Cognitive psychology: rare items often missed in visual searches. *Nature*, *435*(7041), 439–440. https://doi.org/10.1038/435439a

Wolfe, J. M., Horowitz, T. S., Van Wert, M. J., Kenner, N. M., Place, S. S., & Kibbi, N. (2007). Low target prevalence is a stubborn source of errors in visual search tasks. *Journal of Experimental Psychology. General*, *136*(4), 623–638. https://doi.org/10.1037/0096-3445.136.4.623

Yashar, A., & Lamy, D. (2011). Refining the dual-stage account of intertrial feature priming: Does motor response or response feature matter? *Attention, Perception,* *and Psychophysics*, *73*(7), 2160–2167. https://doi.org/10.3758/s13414-011-0182-y

Yashar, A., Makovski, T., & Lamy, D. (2013). The role of motor response in implicit encoding: Evidence from intertrial priming in pop-out search. *Vision Research*, *93*, 80–87. https://doi.org/10.1016/j.visres.2013.10.014

Zhao, J., Al-Aidroos, N., & Turk-Browne, N. B. (2013). Attention Is spontaneously biased toward regularities. *Psychological Science*, *24*(5), 667–677. https://doi.org/10.1177/0956797612460407