

Rare, but obviously there: Effects of target frequency and salience on visual search accuracy[☆]



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ABSTRACT

Accuracy can be extremely important for many visual search tasks. However, numerous factors work to undermine successful search. Several negative influences on search have been well studied, yet one potentially influential factor has gone almost entirely unexplored—namely, how is search performance affected by the likelihood that a specific target might appear? A recent study demonstrated that when specific targets appear infrequently (*i.e.*, once in every thousand trials) they were, on average, not often found. Even so, some infrequently appearing targets were actually found quite often, suggesting that the targets' frequency is not the only factor at play. Here, we investigated whether salience (*i.e.*, the extent to which an item stands out during search) could explain why some infrequent targets are easily found whereas others are almost never found. Using the mobile application *Airport Scanner*, we assessed how individual target frequency and salience interacted in a visual search task that included a wide array of targets and millions of trials. Target frequency and salience were both significant predictors of search accuracy, although target frequency explained more of the accuracy variance. Further, when examining only the rarest target items (those that appeared on less than 0.15% of all trials), there was a significant relationship between salience and accuracy such that less salient items were less likely to be found. Beyond implications for search theory, these data suggest significant vulnerability for real-world searches that involve targets that are both infrequent and hard-to-spot.

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1. Introduction

Visual search—the act of finding targets among distractors—is a common activity conducted countless times every day; people regularly look for specific messages in their E-mail inbox, scan restaurant menus for their favorite meals, and look for their cars in a crowded parking lot. While accurately and efficiently completing such common visual searches is desirable, other search scenarios place a much higher priority on accuracy. For example, airport security screening and radiology demand high search accuracy as their outcomes can have life-or-death consequences. Unfortunately, a variety of factors can negatively influence search accuracy, and thus it is important to understand, and overcome, these influences.

Recent evidence has examined the influence of target prevalence—the likelihood of any target appearing during search—on visual search accuracy. While many laboratory-based search tasks employ a relatively high frequency rate (*e.g.*, most have a target present on 50% of the

trials), many real-world searches—such as airport security screening and radiological cancer screening—are *rare-target searches* in which targets are only present on a very small percentage of trials. For example, the cancer rate in mammography is estimated at less than 5 cancers per 1000 examinations, or approximately 0.5% of cases examined (NCI, 2009). Searchers rarely encounter what they are trying to find when target prevalence is so low, and previous research has suggested that search accuracy is much lower for rarely appearing targets *versus* frequently appearing targets (*e.g.*, Godwin et al., 2010; Hon, Yap, & Jabar, 2013; Menneer, Donnelly, Godwin, & Cave, 2010; Rich et al., 2008; Wolfe & Van Wert, 2010; Wolfe, Horowitz, & Kenner, 2005; Wolfe et al., 2007; but see also Fleck & Mitroff, 2007). This effect has been demonstrated in cancer screening (Evans, Birdwell, & Wolfe, 2013; Evans, Tambouret, Wilbur, Evered, & Wolfe, 2011) and for newly trained airport baggage screeners (Wolfe, Brunelli, Rubinstein, & Horowitz, 2013).

While target prevalence has been the focus of recent investigations, a related influence has gone largely unstudied. Namely, distinct from how often *any* target might appear (*i.e.*, target prevalence), there is also variability across visual search tasks in how often a *specific* target might appear. That is, when there are multiple possible targets that can appear in a search environment, some of those targets may be present relatively more often than others regardless of overall target prevalence. For example, it is rare for any contraband item to appear

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in an airport X-ray image (*i.e.*, there is a low target prevalence rate), but among these targets, some items (*e.g.*, water bottles), are more likely to appear than others (*e.g.*, hand grenades). In this scenario, a water bottle would have a higher frequency rate than a hand grenade. We refer to this particular issue, the likelihood of a specific target appearing during a search as *individual target frequency* (ITF), and note that it is distinct from target prevalence—the likelihood of any target appearing during a given search.

We recently demonstrated that visual search accuracy can be dramatically impacted by ITF rates (Mitroff & Biggs, 2014). In our previous study, we assessed data from the mobile application *Airport Scanner* (Kedlin Co.; <https://www.airportscannergame.com>) to examine search accuracy for 78 unique targets that appeared throughout millions of trials. This immense dataset provided a means to examine the influences of ITF on accuracy across a range of frequency rates (from 0.08% to 3.70%), and for extraordinarily low frequency rates (thirty items had an ITF rate below 0.15%). The evidence showed a strong logarithmic relationship between ITF and search accuracy, with relatively accurate search performance above 1% ITF and a substantial decline in accuracy below 1% ITF. The thirty targets with an ITF rate below 0.15% (*i.e.*, each of the items appeared less than 15 times out of every 10,000 trials), which were referred to as “ultra-rare” items, had an average detection rate of 27%. This was relatively low compared to an average detection rate of 92% for the targets with an ITF rate above 1%. However, some of the ultra-rare items were often found (accuracy rates of approximately 75%) while others were almost never found (accuracy rates below 10%). This variability is intriguing, and it is important to understand why there would be such substantial differences in accuracy for ultra-rare targets. If ultra-rare items are generally harder to find, but some are actually quite easy to find, then determining what drives this variability can inform both search theory and practical implementations for real-world searches that include ultra-rare targets.

The most straightforward possible explanation for why some ultra-rare items may be found more often than others is that they “stand out more.” Saliency—how much an item stands out in a display—is a common concept in attention studies: “high-saliency” is used to describe items that readily stand out, whereas “low-saliency” is used to describe items that do not stand out (*e.g.*, Parkhurst, Law, & Niebur, 2002; Treue, 2003). Notably, differences in target saliency are known to have robust influences on both search speed and search accuracy. For example, a singleton—an item that differs from the rest of the display on a single, basic feature dimension—often can be found very quickly despite many homogenous distractors in the display (Treisman & Gelade, 1980). The important point is that even very similar items could vary in how well they stand out.

Here we asked a simple question: Could saliency explain why some ultra-rare targets are found more often than others? Although ITF and saliency are both potent contributors to visual search accuracy, they have yet to be directly compared. Highly salient targets might be found very quickly and with high accuracy, but does that also mean a searcher would miss an infrequently appearing target no matter how prominent it was in the display? While this is a relatively straightforward question, it is not easily answered in a typical laboratory-based study as it requires a range of target frequencies and saliency levels. With access to a remarkably large dataset from the mobile application *Airport Scanner*, here we investigated the roles of ITF and saliency on visual search performance across 79 different targets that varied in both ITF and saliency.

2. Methods

2.1. Overview

All data reported here came from anonymous gameplay data recorded in accordance with the terms and conditions of the standard Apple User Agreement and those provided by Kedlin Co (<https://>

www.airportscannergame.com). Players voluntarily consented to the terms and conditions upon installing the *Airport Scanner* application, and Kedlin Co. made the data available to our research team for analysis. Approval for research use was obtained from the Duke University Institutional Review Board.

Below we provide specific details about the nature of the data, and more information can be found in Mitroff and Biggs (2014). Broadly, *Airport Scanner* is a game wherein the player serves as an airport security officer and reports the presence of illegal items in bags via finger taps. The player advances through various levels, which provide a variety of influences (both positive and negative) that can affect search accuracy and efficiency. To simultaneously assess the potential roles of both ITF and saliency on search accuracy, we assessed a data pool of 1.1 billion trials. These data were filtered to provide measures of search accuracy, ITF rates, and saliency rates; details on the particular filtering done for each measure are provided in Appendix A.

2.2. Participants

Players of *Airport Scanner* advance through various skill levels, from *Trainee* to *Elite*, and we focused all analyses on data from *Elite* players. This provides assurance that the players had sufficient familiarity with the gameplay as they would have had to complete a minimum of 618 trials to obtain this status (and most had significantly more exposure than this). Data were collapsed across players, and no player-specific analyses were conducted.

2.3. Airport scanner gameplay

Players searched for “illegal” target items and identified targets by tapping a finger directly onto the item. Each search display consisted of a single bag that moved from left to right on a conveyor belt, and each bag contained between 0 and 20 items. Items appeared in one of several different bag types that varied in size, shape, and orientation. See Fig. 1 for examples. A bag contained 0, 1, 2, or 3 “illegal” target items and 0 to 20 “legal” items that served as distractors. There were multiple levels (*airports*), which consisted of multiple sessions (*days*), and each session included multiple trials (*individual bags*). Different levels had different time pressures, and some levels became unlocked based upon successful gameplay. Honolulu and Las Vegas were the two earliest levels and had the slowest conveyor belts (*i.e.*, more time can be spent searching per bag), whereas Chicago had a faster conveyor belt, which increased the time pressure, and London and Aspen had the fastest conveyor belts.

Players could obtain in-game upgrades, and while the upgrades performed a variety of functions, they generally made gameplay easier. As such, we eliminated data that were collected when upgrades were active, except for the *Recharge Boosts*, which helped recharge other upgrades for more frequent use (and thus had no effect on a player's in-game performance), and the *Rare Item Magnet*, which attracted certain targets in gameplay that had special value but were not relevant for, or included in, any of the present analyses.

2.4. Target and distractor stimuli

In the data used for this study, “illegal” targets and “legal” distractors included a total pool of 94 illegal items and 94 legal items that could be present during search. Our analyses focused on the target items that could appear in bags alongside legal distractors without requiring special in-game upgrades to view, which provided a pool of 79 possible target items.

2.5. Accuracy trials

Accuracy data were assessed for trials collected between April 15, 2013, and August 26, 2013. Our data filtering for this project (see

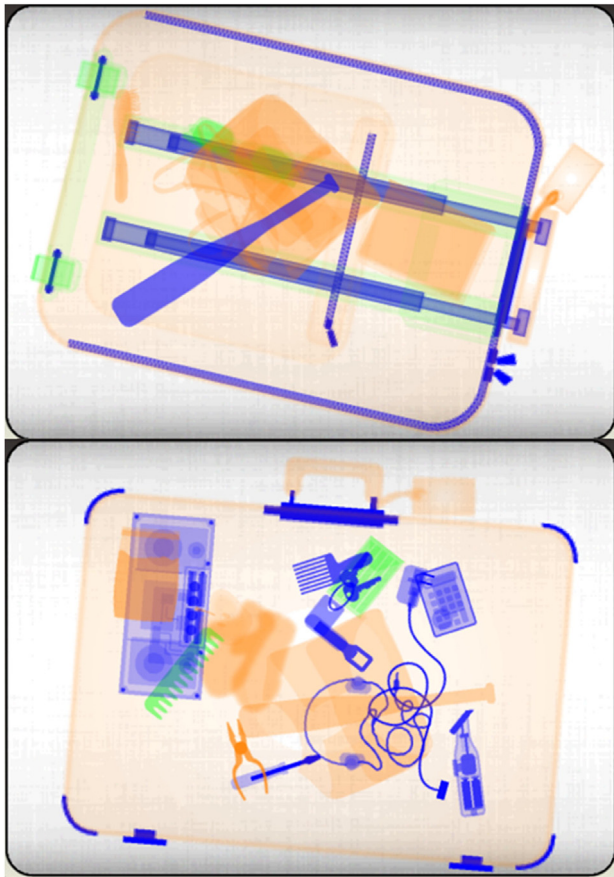


Fig. 1. Examples of a high-salience target versus a low-salience target despite both targets being identical in size and shape. The top picture contains an aluminum baseball bat (pictured in blue), whereas the bottom picture contains a wooden baseball bat (pictured in orange).

Appendix A for a full list) produced an accuracy dataset of 1,795,907 trials. The 79 target items each appeared an ample number of times within this dataset (minimum = 703 trials) to provide stable accuracy rates.

2.6. Individual target frequency (ITF) calculations

Target frequency represents the likelihood of a specific target being encountered during gameplay. Because ITF rates should represent the entirety of target exposures rather than a constrained range best suited for assessing accuracy, we used a broader range of trials than those used to assess accuracy. ITF rates were calculated using all bag types, regardless of whether upgrades were active or not, and for any number of targets present in a single bag (0, 1, 2, or 3). Target frequency rates were calculated from 14,936,601 trials collected from April 15, 2013 to July 9, 2013. This date range slightly differed from the accuracy data date range, as this more limited range provided sufficient data for stable measures of ITF rates.

Global target prevalence—how often any target appeared during search—was 51.03%. ITF rates—how often a specific target appeared during search—ranged from a minimum of 0.078% ($N = 11,704$ appearances) to a maximum of 4.14% ($N = 618,974$ appearances). See Appendix B for full ITF rates.

2.7. Salience calculations

Broadly defined, *salience* denotes how easily an item can be detected in its environment, with high-salience items being relatively easy to find and low-salience items being relatively hard to find (e.g., Parkhurst

et al., 2002). For example, a red square in a field of blue circles would be relatively easy to find, whereas a red square in a field of red rectangles and blue squares would be relatively hard to find. Salience has been defined in a variety of ways in the literature—some studies defined salience via bottom-up contrasts in the display (e.g., Itti & Koch, 2000, 2001; Itti, Koch, & Niebur, 1998; Theeuwes, 1991; 1992), whereas other studies defined salience based upon the current attentional set (Eltiti, Wallace, & Fox, 2005) or personal preferences (Biggs, Kreager, Gibson, Villano, & Crowell, 2012).

For the current study, it is not feasible, or sensible, to define each target item's salience through purely bottom-up or top-down definitions given that the physical context of each trial varied (i.e., each trial had a different set of legal, distractor items present). As such, we operationally defined salience through an objective measure of how easily each target item could be detected; specifically, we measured salience as the average response time to correctly detect a given target when it was the only target present on a trial. Items that are relatively easy-to-spot (i.e., high salience) will have a shorter average response time for detection than items that are relatively hard-to-spot.

In calculating salience, we applied the same data filtering steps as were done for calculating accuracy (see Appendix A). Moreover, to provide the most objective measure of salience via response time as possible, we included several additional filters; we included trials 1) in which the target was detected, which provided a valid response time measure for the given target; 2) in which there were 13 or fewer legal items present to minimize the influences of occlusion and clutter; and 3) from only the first two gameplay levels (Honolulu and Las Vegas) because they imposed the least time pressure and therefore allowed us to see a wider variance in response time.

Salience data were collected from gameplay data between April 15, 2013, and November 17, 2013. This date range was extended beyond the range for accuracy trials to increase the size of the dataset given that an item must be found to provide a valid response time. Only items with reliable salience measures were included in analyses, and we determined the cutoff point for reliable salience measures—at least 20 contributing trials—based upon previous research (see Fleck & Mitroff, 2007; Russell & Kunar, 2012; Wolfe et al., 2005, 2007). This cutoff eliminated 3 targets (*doctor's scalpel*, *hobby knife*, and *gun part #3*), leaving 76 targets available for further analyses. See Appendix B for full salience values.

3. Results

For all regression analyses, we assessed outliers based upon a Cook's D greater than 1 (Cook & Weisberg, 1982), but no data points were trimmed due to this criterion. Additionally, we assessed collinearity through the variance inflation factor (VIF) when two factors were present in analyses, although we never observed a VIF above 10—which indicates that collinearity was not an issue for any of our regression models (O'Brien, 2007).

3.1. Accuracy variance for full dataset: target frequency versus salience

The main goal of the current study was to explore the effects of individual target frequency (ITF) and salience on accuracy to understand what factor(s) most influenced visual search accuracy. Our previous study (Mitroff & Biggs, 2014) demonstrated a significant logarithmic relationship between ITF and accuracy, and as such, we had an *a priori* reason to investigate non-linear trends between ITF and accuracy (cf. Wolfe, 2012). We replicated that finding here, demonstrating that a logarithmic trend best described the relationship between ITF and accuracy (see Fig. 2; Adj. $R^2 = 0.60$, $F(1, 77) = 115.44$, $p < .001$; linear trend: Adj. $R^2 = 0.44$, $F(1, 77) = 63.12$, $p < .001$; quadratic trend: Adj. $R^2 = 0.59$, $F(2, 76) = 56.01$, $p < .001$). Accuracy remained relatively high for targets with ITF rates above 1%, though accuracy fell substantially for targets below 1%.

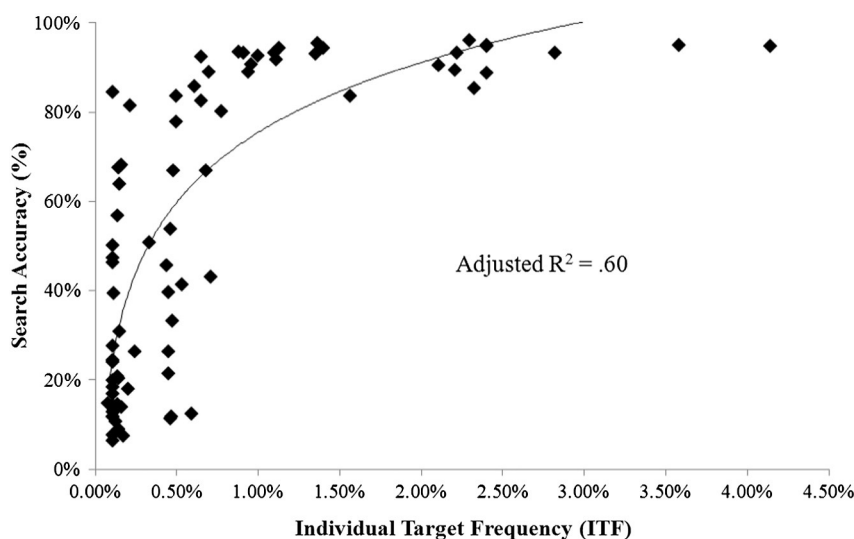


Fig. 2. Hit rate as a function of individual target frequency (ITF) for 79 unique target types. The adjusted R^2 value represents the fit of a logarithmic function (solid line).

Salience was significantly related to accuracy through a linear trend¹ (see Fig. 3; Adj. $R^2 = 0.49$, $F(1, 74) = 73.98$, $p < .001$), such that high-salience targets had relatively higher accuracy rates than low-salience targets. Our primary measure calculated salience from trials containing 13 or fewer distractor items. This approach minimized the role of clutter and occlusions when determining how easily each target item could be detected. We conducted an additional analysis intended to maximize the role of clutter, which represented real-world scenarios where substantial clutter around the target and/or occlusions could mask landmark features (e.g., only the barrel of the gun might be visible in an X-ray image with the handle and trigger occluded). The alternative analysis used a salience measure with all the same data filters and requirements as our previous measure, except limited to trials with 14 or more distractor items present alongside the target instead of 13 or fewer distractors. The relationship between salience and accuracy remained significant under these circumstances (Adj. $R^2 = 0.36$, $F(1, 76) = 44.70$, $p < .001$), demonstrating that target salience and search accuracy were related even with masked or occluded target items.

Before contrasting ITF and salience to determine if one presents a larger influence on visual search accuracy than the other, it is necessary to address a potential concern about the independence of ITF and salience. Specifically, searchers may prioritize targets that appear more often, and consequently, these targets would be found faster than less frequently appearing targets. This could “contaminate” our salience measure with an influence of ITF. This idea was supported by a significant correlation between ITF and salience, $r(74) = -.53$, $p < .001$, which indicated that a target was likely to be found faster if the target appeared more often. To account for this potential influence, we compared salience and accuracy as a direct relationship *versus* the

same comparison with the contributing influence of target frequency removed. As a direct relationship, the correlation between salience and accuracy was significant, $r(74) = -.71$, $p < .001$. To account for the potential influence of target frequency, we conducted a partial correlation between salience and accuracy when controlling for target frequency. Although there was a small decline in the magnitude of the relationship between salience and accuracy, it remained highly significant when controlling for ITF, $r(74) = -.56$, $p < .001$. Thus, target frequency may contribute to the salience measure, but the two still represent independent influences upon variance in search accuracy.

To address whether ITF or salience is the dominant influence on visual search accuracy, we performed regression analyses on search accuracy with ITF and salience as the contributing factors, using the 76 target items that had valid measurements for both ITF and salience (see Table 1). Model 1 represents a reproduction of the above ITF regression analysis, except with 76 target items instead of the 79 target items in the first analysis, and it produced very similar results (logarithmic trend: Adj. $R^2 = 0.58$, $F(1, 74) = 104.29$, $p < .001$; linear trend: Adj. $R^2 = 0.44$, $F(1, 74) = 58.75$, $p < .001$; quadratic trend: Adj. $R^2 = 0.57$, $F(2, 73) = 51.31$, $p < .001$). Model 2 represents a reproduction of the above salience regression analysis (Adj. $R^2 = 0.49$, $F(1, 74) = 73.98$, $p < .001$). Model 3 represents a regression to examine the combined influences of ITF and salience. These two variables predicted a significant amount of variance in accuracy (Adj. $R^2 = 0.70$, $F(3, 72) = 57.97$, $p < .001$; ITF: $\beta = .509$, $t(73) = 5.64$, $p < .001$; salience: $\beta = -.437$, $t(73) = 5.18$, $p < .001$; interaction term: $\beta = -.049$, $t(73) = 0.64$, $p = .52$). The key aspect for our interpretations involved the standardized beta weights associated with these two factors, which provided a comparable estimate for factors measured on two different scales. ITF produced a larger beta weight than salience, suggesting that ITF had a larger influence upon search accuracy. Visual salience still played a significant role in determining search accuracy, although it accounted for a smaller portion of the variance.

To further assess the relationship between ITF and salience, we redid the above analysis but with only “cluttered” trials—those that contained at least 14 distractor items alongside the target. This approach provided a direct comparison of ITF and salience, though under conditions where clutter and occlusions could mask landmark features of the items—as might be seen in airport baggage screening. As for the trials with 13 or fewer distractor items, the model demonstrated that ITF and salience predicted a significant amount of the variability (Adj. $R^2 = 0.67$,

¹ We also fitted non-linear trends when comparing salience and accuracy. Both a quadratic trend and logarithmic trend were significant when assessing the relationship between salience and accuracy (quadratic trend: Adj. $R^2 = 0.52$, $F(2, 73) = 41.90$, $p < .001$; logarithmic trend: Adj. $R^2 = 0.51$, $F(1, 74) = 79.03$, $p < .001$). Although a quadratic or logarithmic trend explained slightly more variance than the linear trend overall, both appeared driven by one particular data point (and neither trend explained any additional variance beyond the linear trend with this point removed, both $p > .19$). As such, we focused our further analyses and discussion on a linear relationship between salience and accuracy.

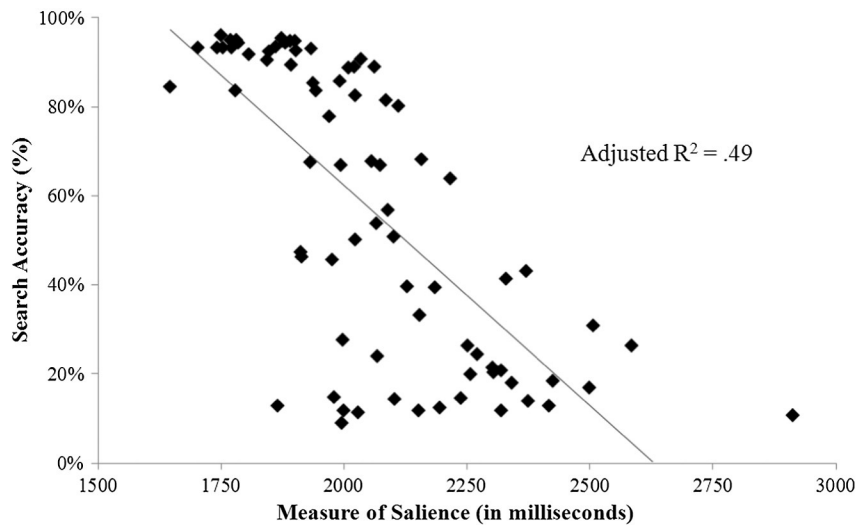


Fig. 3. Hit rate as a function of salience (as measured by response time for accurate target detection) for 76 unique target types. The adjusted R^2 value represents the fit of a linear function (solid line).

$F(2, 75) = 79.73, p < .001$; ITF: $\beta = .627, t(73) = 8.52, p < .001$; salience: $\beta = -.321, t(73) = -4.37, p < .001$). ITF once again produced a larger beta weight, suggesting that it had a larger influence on search accuracy. Moreover, the beta weight differences were more pronounced here suggesting that the role of salience might become further diminished when incorporating additional factors such as clutter and occlusions.

Finally, given the significant correlation between ITF and salience, we conducted a mediator model analysis to differentiate the independent *versus* shared influence of ITF and salience upon search accuracy (Preacher & Hayes, 2004; see Fig. 5). By employing a mediator model here, we were able to assess the influence of ITF upon search accuracy when removing the portion of the shared variance contributed by salience. If salience had a full mediation effect upon the relationship between ITF and accuracy, then there would no longer be a significant relationship between ITF and accuracy when including salience as a mediating variable. ITF and salience both remained significant predictors of search accuracy when controlling for their shared variability, and ITF remained the larger influence of the two (see Fig. 5). The indirect effect (*i.e.*, the influence of ITF on accuracy through salience) remained significant ($\beta = .219$, Sobel test statistic = 3.86, $p < .001$), but smaller than the effect of ITF on accuracy with the mediating influence of salience removed ($\beta = .541, p < .001$).

Table 1

Regression models comparing search accuracy to individual target frequency (ITF) and salience (both independently and together).

Regression model	Statistics		
	β	t	p
<i>Model 1</i> (Adj. $R^2 = .58$)			
Target frequency (ITF) alone	.765	10.21	<.001
<i>Model 2</i> (Adj. $R^2 = .49$)			
Salience alone	-.707	8.60	<.001
<i>Model 3</i> (Adj. $R^2 = .70$)			
Target frequency	.509	5.64	<.001
Salience	-.437	5.18	<.001
Target frequency * salience	-.049	0.64	.52

3.2. Accuracy variance for ultra-rare targets

The above analyses focused on the full range of target frequencies, and demonstrated influences of both ITF and salience on search accuracy. While ITF has a clear influence on search accuracy, it is notable that some of the rarest targets are still found relatively frequently. Here we address whether salience might explain why some targets were found frequently despite having extremely low ITF rates. To examine this question, we limited analyses to only those targets that appeared with extreme rarity (*i.e.*, the 27 items with an ITF rate <0.15%; Mitroff & Biggs, 2014). This removes ITF as a factor since all targets were on the lowest end of the frequency continuum. The ultra-rare items had accuracy rates that ranged between 8.97% and 84.50% (Mean = 31.07%, SE = 4.16%). As seen in Fig. 4 (and in line with our previous work; Mitroff & Biggs, 2014), some of the ultra-rare target items were found quite reliably despite very rarely appearing during search, and other ultra-rare target items were seldom found. Importantly, this variability in accuracy was significantly correlated with salience, $r(25) = -0.49, p = .01$. High-salience targets were found more often than low-salience targets, suggesting that salience plays an important role for accuracy—even for the rarest of rare targets.

4. General discussion

The purpose of the present investigation was to examine how individual target frequency (ITF) and salience influenced visual search accuracy. Specifically, could salience explain why some infrequently appearing targets are found with high accuracy while others are seldom found? Although assessing both factors simultaneously presents an intractable problem for laboratory-based research, we utilized “big data” from the mobile application *Airport Scanner* to assess search accuracy for targets with a wide variety of both ITF and salience. Additionally, given millions of trials for analyses, we were able to investigate differences even among ultra-rare targets—items that appeared on, at most, 0.15% of trials.

We replicated our previous finding of a logarithmic relationship between ITF and search accuracy with a new set of data (*cf.* Mitroff & Biggs, 2014). This pattern (Fig. 2) demonstrates how sensitive search performance is to target frequency. Relatively frequent targets are likely to be found, yet target rarity is highly detrimental to search accuracy. In addition, we observed a significant linear relationship between salience

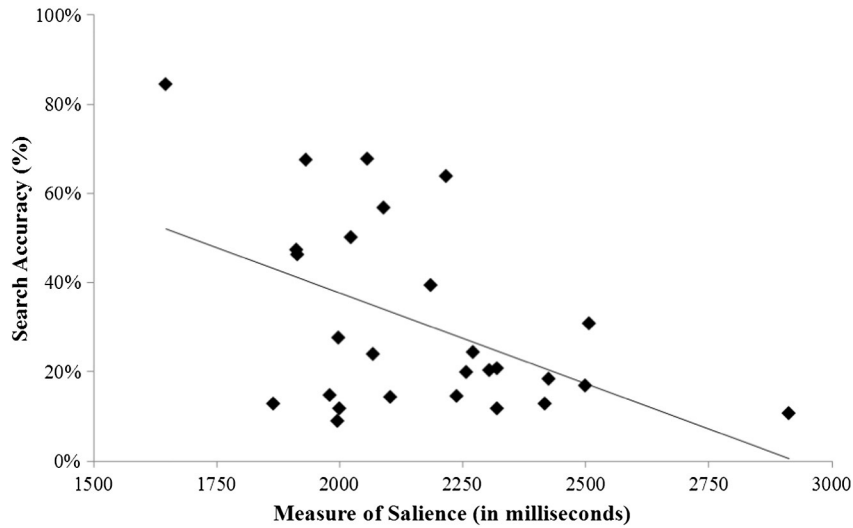


Fig. 4. Hit rate as a function of salience (as measured by response time for accurate target detection) for 27 ultra-rare target types. The correlation coefficient represents the fit of a linear function (solid line).

and accuracy (Fig. 3), such that high salience indicated higher accuracy. This evidence replicates previous findings that salient targets are more likely to be found than non-salient targets (e.g., Biggs & Mitroff, 2013; Cain, Adamo, & Mitroff, 2013; Cain, Dunsmoor, LaBar, & Mitroff, 2011; Fleck, Samei, & Mitroff, 2010). However, while both ITF and salience were prominent predictors of search accuracy, ITF explained more variability in accuracy than salience.

When assessing the role of ITF and salience in predicting accuracy, we were able to account for a variety of factors, although it is important to note that we could not address all. In particular, target and distractor items in the *Airport Scanner* gameplay were always drawn in the same two-dimensional picture plane orientation. Targets could be partially masked or occluded by the numerous distractors, yet there was no three-dimensional rotation in the depth plane. This resulted in all items being displayed from a single viewpoint that was generally a canonical view—albeit with a random two-dimensional rotation. Previous research has demonstrated an increased difficulty in recognizing prohibited items in X-ray images when they are presented in a non-canonical view (Bolfing, Halbherr, & Schwaninger, 2008; Koller, Hardmeier, Michel, & Schwaninger, 2008; Schwaninger, Hardmeier, & Hofer, 2004), but we were not able to test for this factor here. That said, we were able to indirectly address this question through analyses that focused only on “cluttered” trials with 14 or more distractor items present. These trials had an increased likelihood of the target

items being occluded, which can serve as a proxy for non-canonical views as landmark features of the items are more likely to be masked. These analyses supported the conclusions that ITF played a larger role in predicting accuracy than salience.

Additionally, target prevalence—the likelihood of any target appearing during search—did not differ across the *Airport Scanner* gameplay as approximately 50% of the trials included at least one target. Given that target prevalence remained constant throughout gameplay, it is not possible to assess whether prevalence interacts with the impact of ITF rates on search accuracy. For example, it would be interesting to explore whether the influence of ITF rates on accuracy would increase or decrease when global target prevalence was very low. This issue is beyond the scope of the present study, although it is worth noting that such an investigation likely necessitates the use of “big data” platforms such as the *Airport Scanner* mobile application.

The current results demonstrated that ITF was a larger influence on search accuracy than salience, but why might this be the case? One possibility is a “bottom-up” explanation based upon rapid learning through the synchronized firing of neurons (e.g., Masquelier, Guyonneau, & Thorpe, 2008). When a visual stimulus is repeatedly experienced, the systematic firing patterns associated with that particular visual input are strengthened and then require less information to reliably fire at a future presentation. This could create a situation that fits well with our observed data—frequently appearing items are found more easily due to an increase in their representational state. Another possibility is a more “top-down” explanation wherein ITF influences what targets a searcher prioritizes during search, which consequently alters what an individual expects to find. For example, if searchers expect to see more water bottles than guns, they might prioritize finding water bottles and put less effort into locating guns. The end result is that ITF has a direct influence on a searcher’s global priorities.

The present investigation also examined whether salience could explain why some ultra-rare targets were found with high accuracy while others went largely undetected. The initial evidence indicated a strong relationship between salience and accuracy across all targets, where salient targets were more likely to be found than non-salient targets. By comparing items with similar ITF rates (i.e., all very rare items), we were able to control for ITF and examined the relationship between salience and accuracy for only a specific portion of the target set. The significant relationship between salience and accuracy held even when target frequency was limited to only the rarest target items (i.e., less

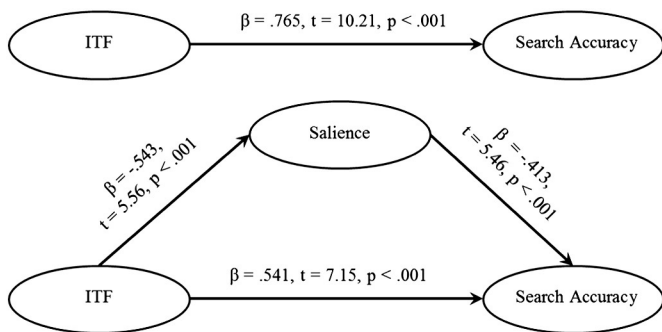


Fig. 5. A mediator model which describes the relationship between ITF and search accuracy when controlling for the influence of salience.

than 0.15% ITF; appearing less than 15 times in 10,000 trials), which indicates that salient ultra-rare targets were still found with relatively high accuracy rates. In practice, this finding suggests that searchers may still find rare and/or dangerous items in professional search tasks if those items stand out.

Given the high accuracy for salient, ultra-rare targets, we can make several inferences about visual search for this class of targets. Foremost, salience is at least partially capable of overcoming the detriment imposed by visual search for infrequent targets, even if salience does not have as robust an influence as ITF across a wide variety of targets. This finding has implications for the types of errors likely to be made during visual search for infrequently appearing targets. For example, because a searcher will likely identify a salient target no matter how infrequently it appears, a failure to find such targets could signify a vigilance and/or fatigue concern (e.g., Grier et al., 2003; Helton & Warm, 2008) rather than anything specific about visual search abilities.

In professional search, this evidence could provide a prioritization plan for professional searchers as the low-salience, low frequency targets are the ones in greatest danger of being missed during visual search. Unfortunately, certain targets—especially in professional visual search—cannot have their salience manipulated on a case-by-case basis, yet research efforts could be geared towards finding technological means to alter either target frequency or the visibility of certain materials. For example, the U.S. Transportation Security Administration uses the *threat image projection* program to project images of threatening items into passengers' bags at airport checkpoints (Hofer & Schwaninger, 2005). This system can be manipulated to present relatively more cases of the especially infrequent and low-salience items (that present the greatest risks to security) to artificially affect the screeners' exposure levels. In addition, it is also possible to artificially alter salience by augmenting search with color filters for certain materials (Abidi, Zheng, Gribok, & Abidi, 2006).

In conclusion, the present findings offered insight into visual search for targets that infrequently appear. Both target frequency and target salience impacted search accuracy, but at least for the data analyzed here, target frequency had a greater impact. Whether or not salience might prove to be the larger predictor of search performance in other experiments, the current investigation demonstrated that searchers do not automatically prioritize salient targets. In addition, this study demonstrated that high salience can sometimes overcome a performance detriment imposed by an item's frequency rate such that infrequent high-salience targets were still detected with acceptable accuracy. Based on this evidence, it appears that the greatest concern for miss errors in visual search might be infrequent and low-salience targets.

Appendix A. Data filtering for calculations of search accuracy, individual target frequency, and salience

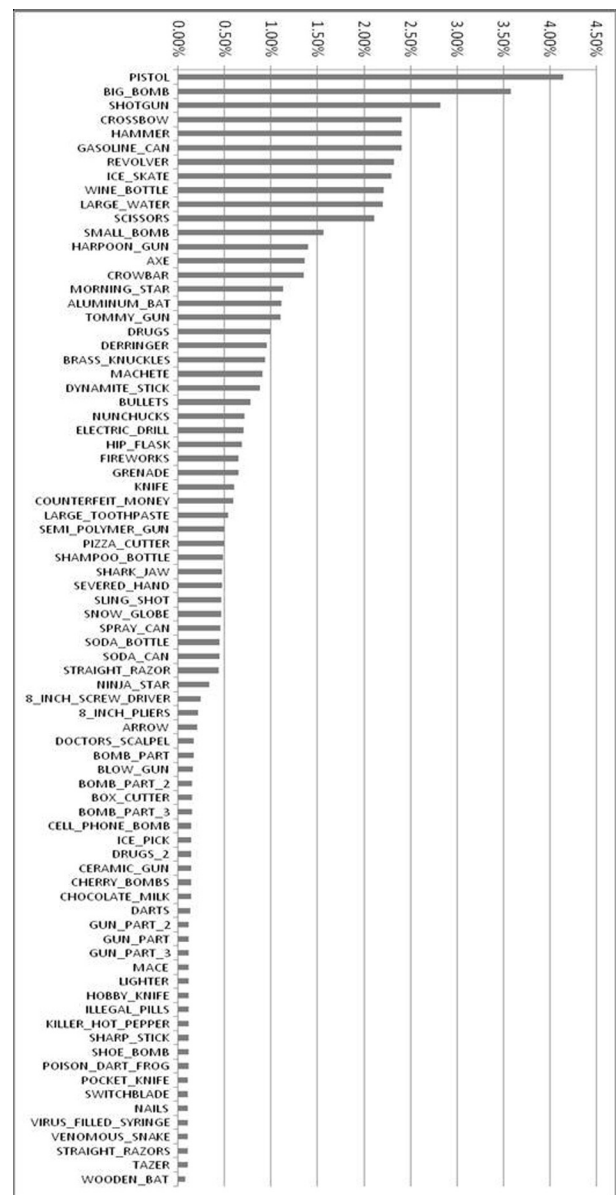
	Target frequency		
	Accuracy	(ITF)	Salience
Number of trials for analysis	1,795,907	14,936,601	1,615,852
Date range of collected data	April 15, 2013 to August 26, 2013	April 15, 2013 to July 9, 2013	April 15, 2013 to November 17, 2013
Data filters applied	<ul style="list-style-type: none"> Only <i>Elite</i> players Only single-target bags 	<ul style="list-style-type: none"> Only <i>Elite</i> players Any number 	<ul style="list-style-type: none"> Only <i>Elite</i> players Only single-target bags

Appendix A (continued)

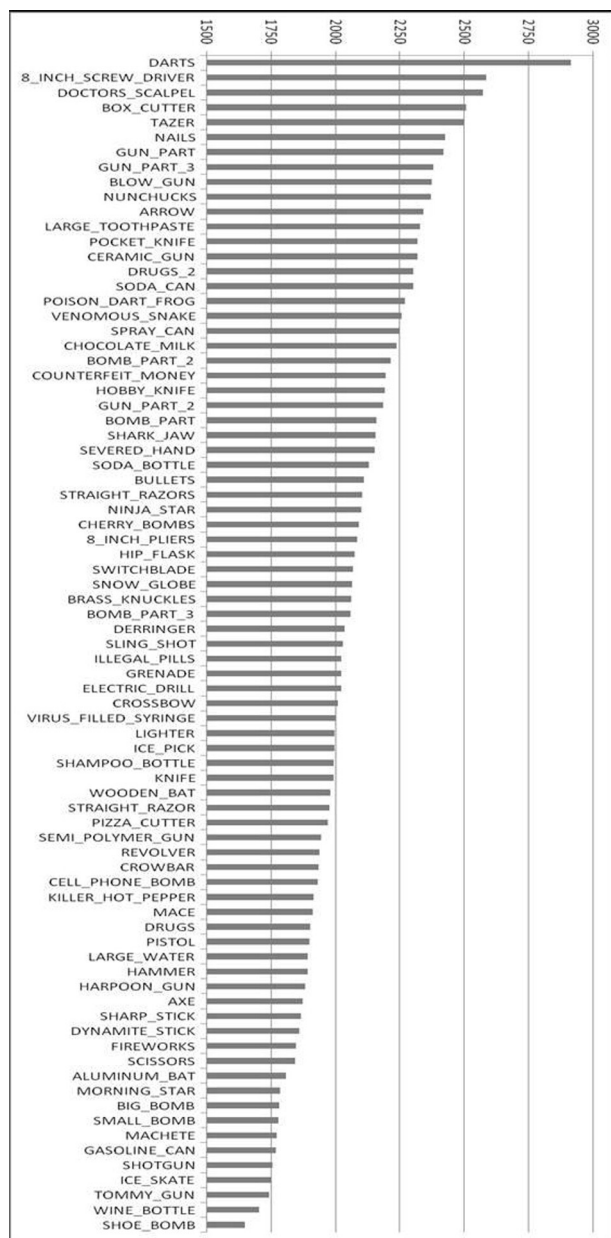
A- A- p- p- e- n- d- ix B. I- n- d- i- v- i-	Target frequency		
	Accuracy	(ITF)	Salience
	<ul style="list-style-type: none"> Only bags with 1 or more legal distractors Only three allowable upgrades (<i>Recharge Boosts and Rare Item Magnet</i>) No <i>air marshals</i> No "Rare" items 	<ul style="list-style-type: none"> of targets Any bag Any upgrades allowed "Rare" items allowed 	<ul style="list-style-type: none"> Only bags with 1 or more legal distractors Only three allowable upgrades (<i>Recharge Boosts and Rare-item Magnet</i>) No <i>air marshals</i> No "Rare" items Target must have been found Only bags with 13 or fewer legal distractors Only <i>Honolulu</i> and <i>Las Vegas</i> airports

dual target frequency (ITF) rates and salience measure rates for each target item

ITF rates
Salience measure



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