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Using Cognitive Psychology Research to Inform Professional Visual Search Operations

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Visual search—locating target(s) among distractors—is a common practice that can range in difficulty from trivially easy to nearly impossible. Professional searches (e.g., airport security, radiology) typically are among the most complicated and challenging tasks, and also often among the most important. The current discussion examines empirical findings in the cognitive psychology literature that contribute to professional search operations, with an emphasis on airport security screening. Primarily, this article focuses on multiple ways to achieve optimal proficiency in security screenings, including personnel selection, training, and continuing assessments. Some of the existing best practices include using orthogonal visual search tasks as predictors of future performance (for selection), item-specific training (for expertise development), and annual competency tests (for continuing assessment). Future research opportunities are discussed, with one especially notable area for future research involving how individuals can potentially develop optimal scanning behaviors for professional search.

Keywords: Professional search, Visual search, Airport security, Personnel selection, Training

General Audience Summary

Many professions (e.g., radiology, airport security) demand highly accurate and efficient visual search, which is the ability to locate target items among distractors. For example, radiologists search radiograph X-rays for cancerous tumors, airport security screeners search luggage X-rays for guns, and Marines search roadsides for improvised explosives. Each professional instance provides its own set of challenging circumstances, yet there are certain common elements and best practices that apply broadly across most professional tasks that require visual search. The current discussion addresses the challenges of selecting and developing proficient visual search by covering three core topics, with a focus on airport security screening as a primary example. First, there is the challenge of selecting the best personnel. Some individual differences link various other cognitive abilities to visual search, yet one of the best demonstrated individual differences thus far appears to be visual search performance on another visual search task, even if the stimuli are unrelated. Second, there is the challenge of training novice individuals into professional visual searchers. The current discussion

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addresses several important factors in the training process, including the process of learning to identify critical targets, learning to operate key equipment, and developing optimal scanning behaviors. Recent cognitive studies have advanced the general understanding of the development from novice to expert, yet significant additional research opportunities remain, especially in developing better scanning behaviors. Third, there are continuing performance assessments that are essential to maintaining skill sets throughout a career. Annual competency tests are combined with on-the-job feedback to maintain performance standards within many professional fields, although emerging big-data opportunities can enhance the existing training opportunities. Taken together, this discussion covers the existing cognitive science research and future research opportunities with the potential to improve professional visual search capabilities.

Visual search—the act of finding targets among distractors—is a fundamental ability central to many professional fields. Airport security screeners scan X-ray images of luggage for prohibited items, radiologists scan radiographs for various health issues, Marines search for improvised explosive devices (IEDs) along roadsides, and so on. Each professional scenario brings new challenges and has aspects unique to the specific field. For example, lifeguards may search for signs of motion, or lack thereof, while surveying the water to identify possible drowning victims (e.g., Lanagan-Leitzel, Skow, & Moore, 2015), whereas motion plays a very different role for airport security screeners searching luggage (e.g., Biggs & Mitroff, 2015; but see also Mendes, Schwaninger, & Michel, 2013). Whatever the specific situation, however, professional searches are often critically important as they can have life-or-death consequences. Radiologists missing tumors can mean life-threatening cancer goes undetected, and security screeners missing bombs could threaten air travel. The potentially severe consequences of poor performance make it essential that the personnel are highly competent and well-trained professional searchers.

The goal of the current discussion is to describe the challenges involved when selecting and evaluating professional searchers with respect to developing and maintaining proficient visual search abilities in a professional environment. As such, we will focus on three primary areas: (a) selecting individuals with the optimal predispositions to professional visual search tasks, (b) training individuals for a professional visual search, and (c) maintaining proficiency through continuing competency assessments. Our focus will be on the contributions of cognitive psychology to the greater understanding of professional visual search with a particular emphasis on airport security screening. The discussion will begin with a brief description of the cognitive challenges in professional visual search with the majority of examples coming from airport security.

Differences Between Professional Search Tasks and Everyday Search Tasks

Many everyday tasks involve visual search (e.g., people look for their shoes in the morning, a particular message in their email inbox, and their kids at the playground). Even so, such everyday searches are often substantially less complex and less critical than searches conducted by professionals (Biggs & Mitroff, 2015; Hodgetts, Vachon, Chamberland, & Tremblay, 2017). In the example of people searching for their shoes, searchers have knowledge about what the shoes look like, where they usually are, that there should be two shoes, and a wealth of other contextual information that reduces task complexity. Moreover, there are widely variable time pressures for people to find their shoes, and a high likelihood of success. In contrast, an airport security officer faces great time pressures and many potential obstacles to success: not knowing if there is a prohibited item packed in a particular bag, where the item would be, what the item is, and if additional items might also be present.

While there are many ways to categorically divide everyday and professional searches, one overarching difference is that professional searches often involve a higher level of uncertainty. Whereas everyday searches can usually be titrated down to the search for a specific target in a specific scenario, professional searches are often more noisy and ambiguous. This difference highlights a potential disconnect between cognitive psychology research and real-world visual search; specifically, a core concept in the cognitive psychology literature suggests that visual search can be driven by the formation and use of "target templates"—mental representations searchers use to distinguish target items from distractors during search (Vickery, King, & Jiang, 2005). These representations can consist of detailed visual information (e.g., Vickery et al., 2005) or categorical information (Yang & Zelinsky, 2009).

The underlying and well-replicated concept is that greater specificity in the target template produces better visual search speed and accuracy (e.g., Bravo and Farid, 2009, 2012; Malcolm & Henderson, 2009; Schmidt & Zelinsky, 2009). For example, a searcher will find a target faster and more accurately if they search for a blue square versus any blue shape. However, imprecise target templates are an unfortunate and almost unavoidable demand for many professional search tasks. Security officers will have a good understanding of potential prohibited items, but the list is often extremely long (guns, knives, bombs, etc.) and the searcher does not know what items (or what exemplars of those items) will be present on any given search. Unlike two potential targets in a laboratory visual search task, two prohibited items at a checkpoint are not given the same consideration. For example, missing a screwdriver could be problematic, but missing an IED could be catastrophic. This distinction creates a type of hierarchy among items, where guns, knives, and IEDs are prioritized over other less threatening targets such as pliers or a hammer.

As such, the main target categories are relatively limited, yet each target type includes an exceptionally long list of individual exemplars. The target categories are further complicated by the potential for item overlap or target camouflage. Explosives could be built into electronic devices to disguise their appearance (Howell, 2017), whereas laboratory-based experiments almost always provide adequate separation between items on a level plane (for further discussion, see Godwin et al., 2017). All of these challenges are further compounded and ever evolving due to thinking adversaries who add to potential targets by developing new techniques to evade detection, which stands in sharp contrast to virtually all laboratory-based research. These combined task demands create a bench-to-field challenge where strong and reproducible laboratory-based findings are limited in transfer to field-based applications (for further discussion, see Clark, Cain, Adamo, & Mitroff, 2012).

Beyond having a varied number of potential targets and systems to learn, professional visual searches often involve rarely present targets—particularly in airport security screening and radiology, targets (thankfully) do not appear very often. However, when a target only appears on a small percentage of trials (e.g., less than 10%), search accuracy drops off substantially as compared to the 50% prevalence rate commonly used in laboratories (e.g., Wolfe, Horowitz, & Kenner, 2005; Wolfe et al., 2007; but see Fleck & Mitroff, 2007). This is an important issue for many professional search tasks with critical life-or-death implications. For example, while prohibited item rates are not publicly available for airport security, the estimated breast cancer rate in mammography is 4.69 cancers per 1000 examinations—approximately 0.5% of cases examined (Breast Cancer Surveillance Consortium, 2009). Overall target prevalence (i.e., how often *any* target appears) is further complicated by individual target prevalence (i.e., how often a *specific* target appears), with substantially lower accuracy when particular targets have exceptionally low appearance rates (Mitroff & Biggs, 2014). While there are some hints at interventions to counteract the effects of low prevalence (e.g., Wolfe et al., 2007), perceptual failures persist (e.g., Godwin, Menneer, Riggs, Cave, & Donnelly, 2015; Hout, Walenchok, Goldinger, & Wolfe, 2015). Whether through early termination errors or perceptual failures, the robust finding is that searchers are less likely to find a target if that target, or target type, rarely appears.

Another particularly thorny challenge for professional searchers is that their search can contain more than one target. Multiple-target search introduces an additional source of error wherein finding one target reduces the likelihood of finding additional targets in the search (e.g., Fleck, Samei, & Mitroff, 2010; Smith, 1967; Tuddenham, 1962). This has been well examined in radiology (e.g., Berbaum, Franken, Caldwell, & Schartz, 2010) and recent work from cognitive psychology has focused on elucidating the underlying mechanisms (e.g., Adamo, Cain, & Mitroff, 2013; Biggs, Adamo, Dowd, & Mitroff, 2015). While there are some solutions that can minimize this negative impact of multiple targets on search performance (e.g., Cain, Biggs, Darling, & Mitroff, 2014) this issue can directly impact airport security screenings (Mitroff, Biggs, & Cain, 2015).

Collectively, these various challenges have one underlying aspect in common—uncertainty. With professional search tasks, the searcher must simultaneously consider a myriad of possible targets often with complete uncertainty as to which target will be present on any given search, when targets will occur, or even how many targets will be present. Uncertainty undermines search performance, which creates a massive obstacle in professional visual search.

The First Step Toward Competency: Selecting the Right Personnel

The above discussion highlights that professional search operations face immense challenges related to uncertainty. To overcome such challenges, professional organizations must enact practices that provide the best chances of success. One solution involves better hiring criteria—that is, find people predisposed to be good searchers and they should develop more readily into professional searchers. From a theoretical standpoint, there should be some people who are better at visual search given that there are individual differences in basic search competency (e.g., Joseph, Keehn, Connolly, Wolfe, & Horowitz, 2009; O'Riordan, 2004; O'Riordan, Plaisted, Driver, & Baron-Cohen, 2001; Plaisted, O'Riordan, & Baron-Cohen, 1998). As such, it should be possible to use certain individual differences to identify personnel best suited to conduct professional visual search. Below we discuss some of the cognitive research into individual differences that offers insight into predicting visual search competency.

The fundamental argument here is that some aspects of visual search are basic, core cognitive abilities. This stance suggests two important assumptions: first, that there are individual differences in search performance, and second, that visual search competency is stable within an individual (but can be altered via training). Prior research provides support for these ideas in a variety of ways. First, individuals who are good at one visual search task tend to be good at other visual search tasks (see Figure 1 for exemplar visual search task stimuli); for example, the best predictor of low-prevalence visual search accuracy is high-prevalence visual search accuracy (Peltier & Becker, 2017a). Likewise, accuracy on a simplified visual search task was found to correlate with accuracy for checkpoint X-ray screening among professional aviation security officers (Hardmeier, Hofer, & Schwaninger, 2005; Hardmeier, Hofer, & Schwaninger, 2006; Mitroff, Ericson, & Sharpe, 2017). Second, individuals who start out performing a search task well maintain their relative high level of performance over other individuals—those who are initially better than others at a search task remain better than others much later in the same task (Ericson, Kravitz, & Mitroff, 2017). Finally, individual and even cultural differences in eye movements have similar effects on performance across a wide variety of information processing tasks as well as visual search (e.g., Andrews & Coppola, 1999; Rayner, Li, Williams, Cave, & Well, 2007). Collectively, these data (and more) suggest that visual search is a cognitive ability that can be identified through stable individual differences.

If stable individual differences can identify individuals who are (or at least are likely to be) better visual searchers, the question becomes how best to leverage this information to improve professional visual search. Several research lines suggest that a simple visual search task can help with personnel selection.

First, since performance in one type of search task can predict performance in another search task (Peltier & Becker, 2017a), a standardized search task can be administered to potential employees to assess abilities. Second, since simplified search tasks can relate to on-the-job performance metrics of professional airport security officers (Hardmeier et al., 2005, 2006; Mitroff et al., 2017), it might be possible to leverage the performance on a simple task to predict whom to select. Finally, since early performance in a search task can predict later performance in the same task (Ericson et al., 2017), it should be possible to extrapolate later success from a preliminary test.

The ability to identify superior performers may be bolstered by supporting evidence from non-visual search tasks, as other cognitive abilities have been linked to visual search performance. For example, search performance has been linked to figure-ground segregation, logical reasoning, mental rotation, and spatial imagination (Bolfing & Schwaninger, 2009; Hardmeier & Schwaninger, 2008), and working memory capacity is strongly associated with visual search (e.g., Lavie & De Fockert, 2005; Poole & Kane, 2009; Roper, Cosman, & Vecera, 2013). Both abilities represent cognitive elements that may be able to predict search performance despite their assessments not actually involving a visual search task. Some evidence already exists to support this idea, such as how working memory capacity has predicted search accuracy in low prevalence visual search (e.g., Peltier & Becker, 2017b; Schwark, Sandry, & Dolgov, 2013) and the contents of working memory can impact search performance (e.g., Dowd & Mitroff, 2013). In practice, using non-search cognitive predictors is an intriguing idea for selecting the best personnel, albeit the evidence remains preliminary at this point and more detailed work is required before using these predictors as selection criteria for professional visual search.

In addition to cognitive factors, personality differences are intriguing possible predictors in identifying good visual searchers. However, while personality traits are commonly used in organizational settings to predict future performance (e.g., Ones, Dilchert, Viswesvaran, & Judge, 2007), there is far less cognitive psychology work examining the relationship between personality factors and visual search. Still, one study found that extraversion predicted accuracy in low prevalence search, but its predictive power was relatively minor compared to high prevalence search accuracy and other cognitive factors (Peltier & Becker, 2017a). In another study, conscientiousness was identified as a predictor of search accuracy among professional searchers, although the effect was limited to early-career professionals and not more experienced professional searchers (Biggs, Clark, & Mitroff, 2017). The latter evidence is noteworthy for being collected from professional searchers who regularly perform airport security screenings. Unfortunately, given the limited evidence, few strong conclusions can be drawn at this point regarding whether personality factors are sufficient for personnel selection in professional visual search. The more reliable factor for predicting later success (i.e., informing personnel selection), for the moment, appears to be simplified versions of the search task in question.

The Second Step Toward Competency: Training Novices to Become Experts

Once preferred candidates have been identified, the next challenge is preparing them for the task at hand. The most obvious professional challenge involves training individuals to recognize specific targets and classes of threat objects (Koller, Drury, & Schwaninger, 2009; Koller, Hardmeier, Michel, & Schwaninger, 2008; Halbherr, Schwaninger, Budgell, & Wales, 2013). Different professions inherently have different task demands and different targets to find, which can create virtually no overlap in the targets searchers are trained to identify. Part of the challenge is then learning to identify the myriad of items that should be found. Moreover, each particular item can appear in many

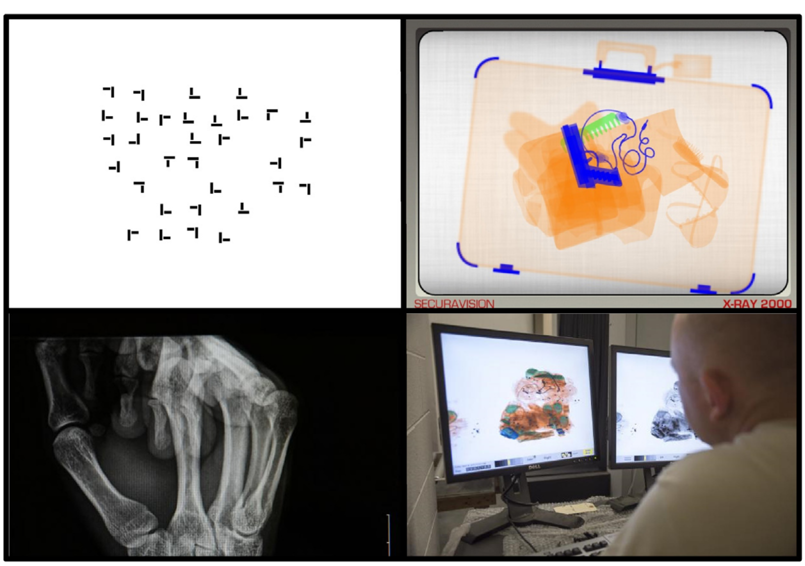

Figure 1. Examples of visual search stimuli, including typical T and L stimuli in laboratory experiments (top left; e.g., Biggs et al., 2013), stimulus from the mobile application *Airport Scanner* (top right; e.g., Ericson et al., 2017), radiology X-ray image (bottom left; photo by Airman BrieAnna Stillman, 20th Fighter Wing Public Affairs), and example baggage screening image (bottom right; photo by Tech. Sgt. David Carbajal, 4th Fighter Wing Public Affairs).

different angles and with varying levels of occlusion or clutter, which makes item-specific training aspects even more challenging. For airport security specifically, three image-based factors likely have the most impact on search success: the angle from which an object is viewed, superposition of irrelevant objects (or occlusion), and the complexity of a given bag or container (Schwaninger, 2003). For example, a knife may be easily identifiable from a side profile, but the blade may be hard to recognize when viewing the edge or when viewing it rotated so that the observer sees a top-down only view (see Figure 2). These challenges are why three-dimensional scanners or systems with multiple viewpoints are particularly appealing—they can lead to higher detection rates when contraband items are rotated in non-canonical manners or occluded by other objects (Franzel, Schmidt, & Roth, 2012; von Bastian, Schwaninger, & Michel, 2011).

Beyond the item-specific challenges of training visual search competency, another, often underappreciated, aspect is how much professional visual search training relies on technology. Any technology platform requires that an individual learn to operate the system—that is, professional searchers must learn how to search with each specific system (and note that systems can regularly change as new advances are introduced) rather than just learning new ways to conduct visual search. A significant training hurdle then becomes establishing effective human–machine interaction when trying to conduct visual search using a particular form of technology, such as an X-ray screener (Michel & Schwaninger, 2009). Training procedures therefore need to include the interplay between identifying specific items and successfully utilizing the technology at hand.

From a technological standpoint, the bulk of training efforts then have to focus upon managing the variety of operational tools available within an X-ray scanner (Wells & Bradley, 2012; Wetter, 2013). Colloquially, this training burden is known as "knobology" (i.e., the study of the machine's components and options). These demands inherently place a cognitive load on the searcher during the learning process that may impact the perceived utility of other examination tools or techniques, yet may not affect the underlying process of learning specific items (cf. Jamniczky et al., 2015, 2017). Unfortunately, any reliance upon technology will be impacted by an upgrade in technology, which could cause a performance decline if the searcher resists or has trouble learning the new system. This possibility is a continuing concern because airport security needs to adapt and evolve to stay ahead of thinking adversaries who continually try to develop new ways to trick or bypass existing technology.

Computer-aided detection (CAD) also has a potentially important role in professional screening tasks such as radiology and airport security. The intent of CAD is to decrease errors by allowing pattern recognition software to identify features of potential targets and bring them to the attention of the searcher (Castellino, 2005). Presumably, the computer could have better raw target detection capabilities (i.e., the signal discrimination portion of signal detection), whereas humans have better decision-making capabilities (i.e., the response criterion portion of signal detection). Optimal performance is supposedly achieved when each element is allowed to impact performance within their best area of influence. Unfortunately, CAD also carries some potential problems. For example, CAD can create an unwarranted sense of certainty in the searcher which leads to incomplete searches or significantly reduced interpretation accuracy (Drew, Cunningham, & Wolfe, 2012; Fenton et al., 2007). Recent research efforts have explored how best to provide information to the searcher, such as how analog information about relative signal strength above a certain threshold produces better search performance than binary marks which give the same signal strength to all stimuli above a certain threshold (Cunningham, Drew, & Wolfe, 2017). Similar future research will be necessary to further improve performance with CAD systems, although one important issue does appear to be how best to provide searchers with information so that CAD does not inadvertently lead to worse search performance than unaided detection.

From a human performance standpoint, the argument here is that the bulk of training efforts should focus on ensuring that an individual is (a) adept at identifying key targets and (b) capable of general skills or strategies that will enable the searcher to find unexpected, new, or strange targets. It is not sufficient to train individuals in identifying targets from canonical and non-canonical viewpoints when new targets can appear at any time. As cognitive research has demonstrated, increased target template specificity will improve search accuracy (e.g., Vickery et al., 2005), but that will not help for varied and new targets which can appear in multiple forms (e.g., an airport security officer must look for any type of firearm, including completely plastic guns made in 3D printers). Although item-specific training (i.e., learning what targets look like) represents the most direct factor in training for professional search, it ultimately will leave the workforce underprepared for varied and novel targets. One alternative approach to this issue is to train security screeners to only identify a bag as harmless if they can say with confidence that every item in the bag is harmless (Sterchi, Hättenschwiler, Michel, & Schwaninger, 2017). This approach produces a criterion shift in decision-making rather than an improvement to target detection abilities (Sterchi et al., 2017), yet it remains a viable method to reduce the rate of missed targets.

To better prepare professional searchers, item-specific training should be accompanied by search strategy training—beyond training *what* to look for, it is also vital to train *how* to search. Critically, a search strategy does not necessarily need to conform to any one specific pattern; rather, the goal is a comprehensive search of the entire display. Unfortunately, visual search is notoriously subject to search lapses or incomplete search patterns because human observers have difficulty remembering what areas they have examined, even within a specific image (Kok, Aizenman, Võ, & Wolfe, 2017; Võ, Aizenman, & Wolfe, 2016). These lapses are even common among professional searchers; as many as one-third of chest nodules in cancer screening could have been missed because the radiologist in question never even looked at them during their search process (Drew et al., 2013). These limitations make training visual scanning behaviors a potential third arm of visual search training to accompany the ability to identify targets and the ability to operate the available technology.

Although there is an evident need for good scanning behaviors in professional visual search, there is little evidence to describe how training for these behaviors should be conducted or even how feedback should be provided. The seemingly obvious approach is to use eye tracking, which allows direct feedback about where a person looked while searching and how long those locations were examined. In theory, eye-tracking feedback should prevent any areas from being overlooked or missed entirely during the search by tracking where searchers have and have not searched. However, in practice, eye movement feedback has yet to yield substantial improvements in visual search accuracy (Drew & Williams, 2017; Peltier & Becker, 2017c). Any performance improvement during training, even short periods of training, appears almost exclusively attributable to improvements in sensitivity to detect targets rather than any notable improvement in scanning behaviors (Krupinski, Graham, & Weinstein, 2013; McCarley, Kramer, Wickens, Vidoni, & Boot, 2004).

Arguably, the most important part of training search strategies may have nothing to do with a specific search strategy at all. That is, feedback and particular patterns may not matter as much as ensuring that a given strategy is being used consistently from one search to the next, as consistent search behaviors may alleviate some of the cognitive burden (Biggs, Cain, Clark, Darling, & Mitroff, 2013; Biggs & Mitroff, 2014; Spain, Hedge, & Blanchard, 2017). As an analogy, consider the cognitive burden of repeating the alphabet. The letters are very difficult to recall out of order (U, S, N, etc.), and very easy to remember when recalled in the usual order (A, B, C, etc.). Repeating the alphabet out of order places a similar cognitive burden as trying to use a chaotic or nearly random search pattern when scanning an image. If the same strategy is used each time, no matter what the specific strategy, then it can eventually become effortless to enact and thereby reduce the cognitive burden on the searcher.

Unfortunately, while consistency has been shown to be a strong predictor of accuracy among highly experienced airport security screeners (Biggs et al., 2013), its value remains more in logical intuition and cross-sectional data than any definitive training paradigm. There is currently little to no evidence regarding the long-term development of consistent search behaviors or detailed proposals as to how consistency should be trained. Additional questions could be raised about the specific cognitive mechanism which underlies any consistency-related improvements in visual search—that is, there is no evidence to support why consistency predicts visual search accuracy. As such, any training conclusions are ultimately premature at the moment as there is no concrete evidence explaining how consistency improves visual search or any clear methods as to how consistency could be trained. If anything, there is evidence to suggest that consistency training could be a complicated endeavor as attentional processes tend to be faster than volitional processes (Wolfe, Alvarez, & Horowitz, 2000). Given the lack of current mechanistic knowledge explaining why consistency improves search and the lack of clear indications on how to train consistency, this area represents great potential for future research that could greatly impact professional visual search. At present, however, the bulk of training will likely continue to rely on learning to identify specific targets from a wide variety of angles and learning to operate any technology available to the searcher.

The Third Step Toward Competency: Continuing Performance Assessments

Assuming success with selection and training, the end result should be a well-prepared workforce able to tackle the challenges of professional visual search. However, skills can atrophy, and this is especially true in an environment like airport security screening where many targets rarely appear. It is conceivable that a searcher will go an entire career without encountering the same model of gun seen during training, let alone from a canonical angle. This example embodies the continuing challenge of professional visual search—years of training and effort go into ensuring that the searcher will be ready when faced with one critical bag.

To address the potential atrophy of skills, two steps are often taken by professional screening organizations: annual competency tests and on-the-job feedback. Annual competency tests are a way to ensure that searchers can accurately perform the task at hand, regardless of how long they have been employed. Although there is substantial variety in specific tests across professions, in airport security these tests and related refresher training generally take the form of computer-based training (CBT). CBT tools can enhance performance by exposing searchers to items they would rarely see at the checkpoint, or by depicting common items as they appear when viewed at non-canonical angles (Halbherr et al., 2013; Koller et al., 2008). Annual competency testing and continuing training are essential because even trained searchers can continue to improve performance as they spend more hours undergoing additional CBT (Michel et al., 2007). On-the-job feedback can supplement annual testing by providing aggregated data for quality control, risk analysis, and individual assessment. This feedback ostensibly supports the annual competency tests by identifying the areas in need of greater focus during refresher training. A prominent airport security method for on-the-job feedback is the threat image projection (TIP) system (Hofer & Schwaninger, 2005), which allows screeners to be exposed to artificial yet realistic targets during normal operations of an airport checkpoint screening. With the TIP system, an artificial image is inserted into bags being scanned for contraband items. Regardless of success, the system provides immediate feedback to the screener, exposes the screener to an increasing number of target items during their actual search duties, and yields quantitative data for risk analysis.

Although factors like CBT and the TIP system are already in place, they can be further supported or enhanced by existing cognitive psychology research. For example, cognitive training only works when the demands are greater than the resources available (Lövdén, Bäckman, Lindenberger, Schaefer, & Schmiedek, 2010). This caveat effectively requires any training system to be adaptive to ongoing individual performance so that the difficulty may be tailored to individual limitations (cf. Schwaninger, Hofer, & Wetter, 2007). Additionally, the TIP system inherently utilizes one of the few approaches previously demonstrated to improve performance in rare-target visual search. Specifically,

Figure 2. Guns (pictured on left) and knives (pictured on right) presented in a bag from canonical views (top images) and non-canonical views (bottom images).

a short burst of high-prevalence target-present trials can reduce the number of misses made when targets rarely appear (Wolfe et al., 2007). The TIP system is designed more for aggregate data than real-time manipulation of searcher expectations, although it is conceivable that the system could be altered to fit multiple purposes.

Perhaps the most intriguing possibility of how cognitive psychology findings can be used to inform personnel assessment systems is taking advantage of the current focus on "big data" research. More and more research is taking advantage of large and varied sets of information to answer questions that would be difficult or impossible to address in typical contexts (see Mitroff & Sharpe, 2017 for further discussion). Big data research has the potential to fundamentally help security screening operations by identifying key aspects related to personnel selection, training, and assessment.

One research line has begun the process of using big data to inform aviation security operations. Specifically, researchers have used data from the mobile game *Airport Scanner* to examine a number of cognitive issues (e.g., Biggs et al., 2015; Ericson et al., 2017; Mitroff & Biggs, 2014). *Airport Scanner* is a game where the player searches through simulated bags for prohibited items. With over 3.4 billion trials of data from over 14 million players, this dataset has been highly fruitful. From an assessment perspective, these data have been used to show that early performance can predict continuing performance many thousands of trials later within the same search task (Ericson et al., 2017). Big data inherently offers more insight about changes in performance because performance assessments can be tracked across time, which makes an individual assessment less subject to unusual variations in performance—such as when an individual who normally performs well underperforms for a given assessment due to lack of sleep, personal problems, or so forth. More directly, a variant of *Airport Scanner* was created under a contract from the US Transportation Security Administration, and it included a brief assessment phase that took approximately 6–8 min to complete (Mitroff et al., 2017). This brief assessment successfully predicted professional screeners' effectiveness (their ability to find real, covert threats) and efficiency (their time to clear bags at the checkpoint; Mitroff et al., 2017). This assessment can potentially be used as an ongoing measure of search competency.

Summary and Future Directions

Professional visual search often involves jobs with a significant impact on public health and safety. As such, every effort should be made to improve their operations. The goal here was to explore how cognitive psychology research can be used to inform personnel selection, training, and assessment for professions that rely on visual search, with a focus on aviation security. While there are obvious ways in which cognitive psychology findings are already being employed (e.g., informing personnel selection via cognitive performance), it is clear that there is much more to come.

From a personnel selection perspective, on-the-job performance could be predicted by factors other than orthogonal visual search tasks, although much more research is needed before solidifying such a stance. Cognitive factors like working memory (e.g., Schwark et al., 2013) appear to be prime candidates for further investigation, and personality factors like conscientiousness and extraversion (e.g., Biggs et al., 2017; Peltier & Becker, 2017b) have some intuitive appeal for different types of search tasks. For example, is conscientiousness a stronger predictor of performance when the search task is relatively difficult (e.g., airport security) compared to a relatively easy search (e.g., Ts and Ls)? Does this difference interact with target prevalence? There are more questions to be asked than have been answered about individual differences in visual search. At this point, a simplified version of the intended search task appears to be a powerful tool for selecting the right individuals to employ (Hardmeier et al., 2005, 2006; Mitroff et al., 2017; Peltier & Becker, 2017a).

From a personnel training perspective, the suggestion here is that traditional training methods which focus on target-specific learning can be complemented with training that focuses on search strategy. Given that professional searches can have novel targets appear at any time, only so much can be gained by overlearning a specific target from a specific view. This idea is a theoretical stance that advocates for generalized training of related cognitive skills. For example, consistency-related training is an intriguing option to improve scanning behaviors, especially given that scanning behaviors can apply across multiple professional tasks with highly varied applications. The current evidence merely argues for a predictive role of consistency in visual search (cf. Biggs et al., 2013) without empirically supporting a mechanism to explain why consistency aids search, which further makes consistency a prime candidate for future research. Given that core cognitive skills can be predictive of visual search skill (e.g., Bolfing & Schwaninger, 2009; Hardmeier & Schwaninger, 2008; Peltier & Becker, 2017b; Schwark et al., 2013), these examples highlight a potential future path for visual search training—focus on core cognitive skills to improve the overall performance of the individual.

From a personnel competency assessment perspective, computer-based training and on-the-job feedback are potentially useful tools in airport security. Annual testing provides the opportunity to ensure appropriate knowledge in identifying rare targets, and cognitive research can both inform and enhance these tests. On-the-job feedback provides a mechanism to improve the annual testing by conducting real-world risk analyses through programs like TIP. Moreover, some targets are so rare that they might not be encountered for years outside of regular training, which further emphasizes the importance of on-the-job feedback for both exposure to rare targets and quality control. Some intriguing and emerging tools to support continuing competency assessments are big data platforms. These systems can provide nuanced insight into security screenings that would be logistically impossible to achieve through laboratory-based means while also providing more insight into an individual searcher. This latter point becomes especially important in distinguishing a trend of poor performance from an outlier performance assessment—good or bad. Accuracy and predictive power should be the goals of a competency assessment, and both factors benefit from information collected through a big data platform.

In conclusion, errors in professional search tasks such as airport security screening or radiology can have life-or-death consequences. Airport screeners who miss an improvised explosive might fail to prevent a terrorist attack, and radiologists who fail to identify tumors might not be able to save a life. Numerous challenges make selection, training, and assessment difficult in these professions, yet these are fundamental aspects that cannot be overlooked. Given the important nature of professional visual search and the vital role of human performance, it is essential that we explore all potential avenues to improve performance, and cognitive psychology research might offer numerous insights that can ultimately improve professional visual search.

Author Contribution

All authors contributed equally to this article.

Conflict of Interest Statement

S. Mitroff is the Chief Science Officer of Kedlin Screening International, a company that has a product focused on personnel selection and assessment.

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