Testing and Training Lifeguard Visual Search

By

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Abstract

Lifeguards play a crucial role in drowning prevention. However, current U.K. lifeguard qualifications are limited in training and assessing visual surveillance skills, and little is known about how lifeguards successfully detect drowning swimmers. To improve our understanding of lifeguard visual search skill, and explore the potential for improving this skill through training, this thesis had the following aims: (a) to identify whether visual skills for drowning detection improve with lifeguard experience, (b) to understand why such differences occur, and (c) design and valid a visual training intervention to improve drowning detection on the basis of these results.

The first two studies investigated drowning-detection skills of participants with differing levels of lifeguard experience in a dynamic search task with simulated drownings. Lifeguards were found to detect drownings faster and more often than non-lifeguards. In three follow-up studies these results were replicated with more naturalistic stimuli. Video footage from an American wave pool was extracted, which showed genuine instances of swimmer distress. Results again demonstrated lifeguard superiority in detecting the drowning targets.

Eye tracking measures, recorded on both the simulated and naturalistic clips, failed to reveal any differences between lifeguards and non-lifeguards, suggesting that superior drowning detection for lifeguards did not result from better scanning strategies *per se*.

Following this, two cognitive mechanisms that may underlie drowning-detection skill were investigated. Lifeguard and non-lifeguard performance on Multiple Object Avoidance (MOA) and Functional Field of View (FFOV) tests was assessed. Although lifeguards had better MOA task performance compared to non-lifeguards, only the lifeguards' accuracy at detecting the central target in the FFOV task predicted performance on a subsequent drowning detection task. It was concluded that superior drowning detection was a result of better classification recognition of drowning swimmers (which was the central task in the FFOV test).

Based on these findings the final experiment explored the effectiveness of an intense classification training task to improve drowning detection. An intervention was designed that required participants to differentiate between videos of isolated drowning and non-drowning swimmers. Non-lifeguards trained in this intervention showed greater improvement on a subsequent drowning-detection task compared to untrained control participants, who completed an active-control task.

The results of this thesis suggest that drowning-detection skill can be reliably assessed, and that foveal processing of drowning characteristics is key to lifeguards' superior performance. Isolating and training this key sub-skill improves drowning-detection performance and offers a method for training future lifeguards.

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- Larkfield Leisure Centre
- Rutland Water Aqua Park
- Gravesham Lifesaving Club
- South Charnwood Leisure centre
- Rushcliffe Areana
- Nottingham City Council Pools

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Chapter 1
Introduction and literature review

This section will provide an overview of the areas of research concerned in this thesis. It will begin by introducing the context and importance of the research topic, in terms of drowning prevention and lifeguarding. A review of the theoretical literature on visual search will then be outlined, first focussing on factors that influence and guide attention during visual search. This overview will then explore factors that make some visual searches more successful than others, with an emphasis on applied real-world domains. Finally, an overview of the literature that has addressed lifeguard visual search and experience effects within lifeguarding will be outlined.

1.1 Introduction

Swimming is a popular activity, but one that can have devastating outcomes. Worldwide it is suggested that approximately 1.2 million people lose their life through drowning, equating to two lives lost every minute (ILSF, 2016). In swimming pools within the U.K, the National Water Safety Forum (2019), who publishes the U.K Annual Fatal Incident Report, document 58 suspected swimming pool drownings between the years 2009-2018.

Long lasting consequences from non-fatal drownings can also occur, which may include permanent brain damage or injury due to prolonged submersion in water. The absolute figures of non-fatal drowning in U.K. swimming pools are unknown, but there is a suggestion that hundreds of individuals each year suffer some form of life changing injury due to these drowning incidents (RLSS, 2016a).

With the severe effects of drowning and non-fatal drowning, it is important to provide measures to help prevent fatalities in the water. These include trained professionals, with lifeguards providing constant surveillance to aquatic areas. The number of drownings in lifeguarded areas is reported to be lower than unmonitored areas, but drowning incidents still occur in lifeguarded zones. It is therefore important to understand the complex task of lifeguard surveillance and the factors that affect visual searches of swimming pools, as failures in surveillance could potentially result in the early signs of drowning behaviours being missed.

1.1.1 The lifeguard role and qualification

Certified lifeguards are individuals who have completed necessary training in lifesaving techniques and have been awarded with compulsory qualifications to supervise aquatic areas. For example, in the UK lifeguards must obtain the National Pool Lifeguard Qualification (NPLQ), or the National Beach Lifeguard Qualification (NBLQ) (RLSS, 2016). In order to qualify as a professional lifeguard, individuals must be competent in a number of rescue techniques and be knowledgeable of lifeguard theory, such as poolside operations. Prior to completing initial training an individual must be able to demonstrate certain skills in the water, such as swimming 50 metres in less than 60 seconds and swimming 100 metres without pause (RLSS, 2016). Currently, there are no requirements or assessments for visual or attentive skills.

While practicing rescue techniques is important, one of the key roles for a lifeguard on a day-to-day basis is to provide constant surveillance to areas of the swimming pool (Lanagan-Leitzel & Moore, 2010). Considering surveillance is one of the important parts of the lifeguard's role, it is surprising that the current examination for the lifeguard qualification does not assess practical surveillance skills. A large focus of the examination is on the ability to perform rescues in the water. Scanning and surveillance knowledge is assessed through a multiple-choice written exam alongside other theoretical questions, such as procedures for evacuation in emergencies, naming the groups of hazards, or first aid knowledge (Blackwell, 2016).

Although there is no formal assessment for surveillance of the swimming pool, lifeguards are taught methods of scanning during training. One of these methods is the 10/20 scanning system. This method prescribes that a lifeguard has 10 seconds to scan their zone of responsibility in search of target behaviours, then 20 seconds to respond to an individual whom they have identified as a potential drowning target (Blackwell et al., 2012).

While there are many successful rescues made every year in UK pools, the scant evidence suggests there is the greatest possibility for delay during the scanning phase of the rescue (prior to identification of a problem). Herrmann and Roberton's (2017) observational study of Danish surf lifeguards found that the time required to detect the target was in some cases nearly double the length of the operational time of the rescue. It was also reported that over 50% of these rescue observation times fell outside of an accepted 2-minute window proposed by the Nordic Lifeguard Organisation (NLO).

1.1.2 Drowning definitions

Early drowning education proposed that a drowning happens in 4 to 6 minutes. This time frame refers to the fact that in this short period irreversible damage occurs to the victim, with vital organs shutting down due to lack of oxygen. Any victim revived after being submerged for over 4 minutes will most likely have permanent brain damage (The National Aquatics Safety Company, 2011). Outcomes of drowning can be either fatal or non-fatal; however, the aftermath of such events can be severe.

Drowning incidents can happen in a variety of different ways, with distressed swimmers in the water showing certain behavioural characteristics. These different types of drownings will be either active (conscious, distressed swimmers) or passive (unconscious swimmers) (American Red Cross, 2012; cf. Idris et al., 2003; van Beeck et al., 2005). Each drowning victim will display their own individual characteristics, showing a variety of behaviours or sometimes no symptoms at all. However, there are some common signs that drowning victims show.

Active (conscious) drowning is commonly characterised by a swimmer in distress. There are certain behaviours that these swimmers display, but typically a silent struggle at the surface of the water will take place and this tends to last for as long as the swimmer's energy permits (typically 20-60 seconds; Pia, 1974). Some stronger swimmers may attempt to continue swimming to the poolside or a shallow location, and some may be able to call out for help. However, in more severe instances instincts take control of an individual's behaviour, resulting in flailing arms, a vertical body position, and head tossed back. These behaviours are collectively termed the *instinctive drowning behaviour* (Pia, 1974); where victims fight to keep the head out of the water, possibly submerging and re-emerging on several occasions, with breathing taking precedence over everything else. Swimmers displaying the *instinctive drowning response* are in immediate danger of slipping under the surface of the water without hope of immediate re-emergence (Vittone & Pia, 2006).

The behaviours of active drowning have been categorised into stages that progress over time and swimming ability (Pascual- Gómez, 2011; Doyle & Webber, 2007). These stages range from a threat to life that is low risk, to a moderate threat and then to one that is an immediate risk to life. Signs range from someone who is in mild distress (may be able to shout for help, and be responsive to commands), to a person showing signs of distress (vertical in the water, but still may able to make forward progress), and then to swimmers who are drowning (displaying the instinctive drowning response). It is important that lifeguards monitor for such behaviours as drowning can quickly progress.

These common behaviours of active (conscious) drownings support the notion that drownings do not happen in a flamboyant manner, with swimmers waving their arms above their head and shouting out for help as often portrayed in the media. Instead, drowning behaviours are potentially silent, with weaker swimmers unable to shout for help as they either gasp for breath or reflexively hold their breath.

While active drowning is commonly characterised by swimmers struggling in the water, passive (unconscious) drownings are those swimmers who have lost consciousness. There is often no struggling involved and the transition from normal swimming can happen quickly. The victim will either slip slowly under the water or remain face down and motionless at the surface. There are a variety of causes of passive drowning, including, prolonged underwater swimming, head injuries or heart attacks (Fenner et al., 1999). Any swimmer showing passive drowning behaviours for longer than 30 seconds should be checked out immediately, as there is a high possibility that they have fallen unconscious in the water (American Red Cross, 2012). At this stage there is an immediate threat to life. These passive drownings are also referred to as unwitnessed drownings, as the victim has potentially passed through the struggling phases of active drowning unnoticed and have fallen unconscious as a result (Idris et al., 2003).

1.1.3 Victim recognition

Drowning victims, whether active or passive will either be at/near the surface of the water, or on the bottom of the pool floor. The transition between the two is relatively quick, with victims on the bottom being in critical danger of permanent brain damage as vital organs start to shut down fast once submerged.

There is also the possibility that a swimmer may already be submerged when the process of drowning begins, such as an individual that has jumped into deep water, or a swimmer diving to the bottom of the pool (American Red Cross, 2012)

Similar to active and passive drownings, victim recognition has also been classified into two types; surface victims and bottom victims (Hunsucker & Davison, 2008). For surface victims, typical characteristics are similar to active drownings, which include; a panicked facial expression, irregular movement through the water (e.g. different from the background swimmers or lack of movement through the water), vertical body position with head thrown back and no supporting leg action, with arms flailing at the side. Surface drowners may also drown passively however, lying motionless at the surface of the water due to unconsciousness. For victims that have sunk to the bottom of the pool, or that are transitioning to the bottom of the pool, typical drowning characteristics include lack of motion and lack of bodily movements, bubbles, a dropped-floppy head and a variation in colour in the pool near the bottom. Victims on the bottom of the pool may be harder to identify as features of the pool (e.g. turbulence, sun glare, or light reflection) may cause blind spots. Therefore, regular systematic search of the pool floor is crucial.

Due to the severity of drowning it is important for lifeguards to keep constant surveillance on their zone. Visual search skills are a critical component of surveillance; skills that result in the lifeguard identifying swimmers in the water that are in danger or are engaging in dangerous behaviours. While there is a limited amount of studies that refer to the visual skills of lifeguards, there is a vast body of literature documenting visual search skills in both laboratory and real-world settings that may help understand the role of surveillance in lifeguarding.

1.2 Theoretical review of Visual Search

Visual search in lifeguarding is defined as the surveillance of part of an aquatic environment, where events happening must be processed and assessed (Lanagan-Leitzel et al., 2015). Within different lifeguarding organisations and countries, the methods of training surveillance differ, but all training providers are working towards the same goal, to reduce and prevent injury and loss of life (Wernicki & Espino, 2013).

Although lifeguarding has been relatively under-researched in an applied domain of visual search psychology, the theoretical underpinnings of visual search may be able to offer some understanding of the complexities of lifeguard surveillance.

In psychology, visual search has been defined as an active scan of a visual scene or array. The scan often involves the detection of a particular object or target amongst an array of other distractors (Snowden, Thompson & Troscianko, 2006). Models of the processes in visual search have been well documented in the literature, with two key mechanisms used to explain successes and failures in visual search: bottom-up and top-down processing (Wang et al., 2016). Bottom-up processing deals with the specific features of the visual stimuli that attract attention exogenously. Processing of search items is independent of the task and attention is stimulus driven, thus the searcher is drawn to attention grabbing objects in the search area. In comparison, top-down processing is dependent on the task, with attention on each search item being selected and controlled in a goal-driven, endogenous process, moving through abstract search arrays in a logical fashion (Wang et al., 2016), or following scene-schema when searching naturalistic images (Foulsham & Underwood, 2011; Henderson, 2003).

Early theories of visual search proposed different types of search, with varying levels of effectiveness and methods of guiding attention to target relevant areas. One of these early theories is the feature integration model proposed by Triesman and Gelade (1980). One component of this model is a feature or parallel search, in which the target and distractors are maximally different in features (e.g. a red square in an array of green squares). This type of search is quick and efficient, with the target having a pop-out effect and searchers using bottom-up salience to guide attention to the specific features of the target (Triesman & Gelade, 1980). Alternatively, there is a conjunction or serial search, which uses top down processing. This involves a more complex search, where targets and distractors share similar properties (e.g. a red square target in an array of green squares and red circle distractors). Due to the target item sharing both colour and shape with the distractors a much slower search is required where the participant searches for a combination of features within a single object (redness and square-ness) (Triesman & Gelade, 1980). Attention is guided through these top-down mechanisms, with the searcher having to pay attention to each of the search items' features.

There are a number of factors that can either help or hinder an individual's search of the visual scene, in both laboratory settings and applied to real world environments. These factors can include theories such as templates and attentional sets, target prevalence and multiple target costs (Schmidt & Zelinsky, 2009; Wolfe et al., 2005; Cain, Adamo & Mitroff, 2013). Furthermore, the brain uses information and knowledge gained from prior experiences to aid in the search for a target object (Bruce & Tsotsos, 2009). There has been extensive research into difference processes that guide attention during visual search and the literature below will discuss what is currently known about attentional orientation in visual search of static displays.

1.2.1 Saliency

Early models of attention in visual search propose the notion of a saliency map (Treisman & Gelade, 1980). This early theory suggests that basic features of an item are extracted from a scene and are then combined to form a topographical representation of saliency. For example, each of the items' features in the search display are used to create separate feature maps. From these maps, the salient items in the scene seemingly draw attention with little effort, which help with efficient searches.

Models of saliency for attention capture have proposed visual processing of solely bottom-up image cues, top-down semantic cues, or a combination of both (Wang et al., 2016). The bottom-up processing of visual attention is a stimulus driven signal that attracts attention to an area of the search display that is sufficiently different from the surrounding locations (salient items), for instance a vertical line in an array of horizontal lines, like Treisman and Gelade's (1980) feature searches. Itti and Koch (2001) have proposed a model of saliency based on bottom-up processing, which offers explanations to understand the processes of where an individual looks within a search scene. This model suggests there is an input stimulus, where an object pops out of the display, involuntarily drawing the observer's attention. The visual features of the pop-out item differ from those of the background distractors in terms of orientation, colour and intensity and these differing features are computed by the brain to create a point on a saliency map. The focus of the searcher's attention shifts from one salient point to the next, in a winner takes all process, which guides the focus of attention to highly salient areas of the visual scene. Once an item has been considered, that point of saliency is inhibited which stops attention being drawn back to the locations that have already been attended to in the search display (Itti et al., 1998). This computational model is used to predict where searcher's attention will be focused in a search scene based on the saliency of the objects.

In an alternate model of search, Wolfe (2006) proposed *Guided Search*, which explains how salient features can be used in a crowded visual array to guide attention. According to this model preattentive information is used first to process basic salient features of the items in the scene array (e.g. colours, shapes). These are done simultaneously across a large area. Once basic features have been extracted, the searcher then uses one or two specific features to search through smaller areas. For example, a person may scan a street for the colour of a friend's shirt, and then focus on the most promising areas to find their face. Therefore, the information from the earlier stage of processing in this model is used to guide attention in the later stage of the search, resulting in a more efficient visual search.

However, Foulsham and Underwood (2011) have suggested that while saliency map models offers an understanding about which targets might be first fixated in a context-free search task, they argued that top-down factors might be more important in determining where we look in the real world. In a series of experiments that manipulated the visual image (periphery features and scene inversion) they noted that the speed with which participants fixate target objects may be more influenced by the meaning of the scene, with advantages in search performance coming from scene knowledge about where to look and what to look for.

In a similar line of research, *the cognitive relevance framework* suggests that cognitive knowledge structures in the searcher's memory interact with task goals, prioritising certain search locations for attention and fixation (Henderson, 2003). In this model the search stimuli and scene are still relevant, with scene objects typically drawing attention over the scene backgrounds. However, the global search scene, the 'bigger picture', allows an individual to access cognitive knowledge structures formed from previous experiences. These cognitive knowledge structures allow for the saliency of an object, in terms of drawing attention, to be overridden by the cognitive information gathered from the scene with attention guided to target-relevant areas. This suggests that attention deployment to each search item is a controlled, selective process, rather than a winner takes all unconscious process.

In a further example, Henderson, Malcolm & Schandl (2009) aimed to understand gaze control using static real-world images of non-salient target objects. It was found that non-salient targets in cognitively relevant areas of the scene were fixated 90-95% of the time, but highly salient targets in cognitively irrelevant areas of the scene were fixated on 8-10% (experiment 1 and 2 respectively). These finding suggest that cognitive knowledge can outweigh the saliency of visual features, guiding eye movements to target-relevant areas. The search for non-salient target items was found to be efficient and fast, with fixations on target items occurring within 3 or 4 saccades. A cognitive-relevance approach was also supported from the results of targets that were fixated upon, with 90% of such target regions being fixated first compared to only 10% of salient (but irrelevant) regions. This suggests that cognitive knowledge is used to guide search to target-relevant areas of the search array.

1.2.2 Scene Context

In real-world search scenes an individual's gaze is often guided to the target based on the search setting and environment, thus targets are expected to appear in logical locations within the scene (Eckstein, 2011). The structure of scenes in applied search settings is referred to as the scene context (Castelhano & Witherspoon, 2016). The definition of scene context incorporates a global view of the scene, where the image is viewed as a whole to gain a general idea of the location of the target (Eckstein, 2011). Objects in the scene can also be used as a guide to focus the searchers' attention during the search for the target, using both knowledge of the target item and the other items in the search scene, particularly those associated with the target, to guide attention and aid detection (Castelhano & Heaven, 2011).

Prior experience with a scene environment allows individuals to make knowledgeable predictions about where an object is likely to be located. This prior experience of the search scene allows gaze and attention to be directed to locations of the search array that have a high likelihood of containing the target item. This has been exemplified in a notable study by Torralba et al. (2006), who showed that when asked to locate a pedestrian, participants typically fixated upon pavements and other areas of the scene where pedestrian targets were likely to be found.

To account for knowledge application in the search scene, Torralba et al. (2006) developed the *Contextual Guidance Model*, a theory which extends the *Saliency Model* through the inclusion of contextual knowledge (scene priors). The contextual guidance model suggests a parallel computation of local salient features and global image features occurs during the search process. One function of the global pathway is to rapidly extract the gist of the scene, allowing prior knowledge to link the target object and scene in order to identify relevant target areas. Using scene priors activates the areas that are likely to hold the target, creating a contextual modulation. The saliency computation from the local pathway is then combined with the global feature contextual modulation, resulting in a scene-modulated saliency map, which guides attention to salient areas where the target is likely to be. The benefit of integrating saliency and scene priors, over and above the use of purely bottom-up salience models, was noted when predicting the location of the target. In integrated approaches, performance reached 83% while a simple saliency model reached 50%.

In a similar model of search guidance, the *contextual cueing paradigm* suggests a learning process occurs where visual information is gained from the items in the search array, which can then be applied to aid target detection (Chun & Jiang, 1998; Chun, 2000). This learning takes place after repeated exposure to a set of target and distractor items in specific arrangements, which results in progressively faster searches over a set of trials (Brockmole et al., 2008). While this paradigm offers insight to visual searches of static images, in real world scenes the items in a search array are often dynamic. One of the problems of dynamic scenes compared to static images is that individuals need to be aware of how objects move in relation to other aspects of the scene over time (Chun, 2000). In an experiment using moving rotated T's in an array of moving rotated L's, Chun (2000) found that when target and distractors' motion trajectories were repeated over trial blocks, participants' target detection speeds were faster than detecting targets with variable trajectories over trial blocks. This suggests that participants can learn and apply the knowledge of dynamic motion contexts in search to help detect the targets, thus repeated exposures allows for cognitive knowledge to be stored in the searchers memory and applied to subsequent target searches, providing subsequent search arrays also contain typical rather than atypical motion patterns.

Recent literature has begun to consider if prior knowledge of a target object's function, and whether the function of that target object relates to its location in a scene, can also be used as a guide to focus the search. Castelhano and Witherspoon (2016) found that the function of the target object did have an effect on where participants searched in the visual scene, with participants being shown a picture of an invented object or given a written description of the objects' functions. In the first of two experiments, the reported scan paths to the target object in this first experiment took a more direct path in trials where the participants had been given a written description of the object's functions (such as: helps people wash themselves, leading searchers to look at the shower area of the search scene), compared to those who only aware of the target objects appearance. In a second experiment, it was found that the function of a target increased search performance when the target was located in corresponding position in the scene. However, when novel items were placed in incongruent locations search performance suffered (for example a novel target that is described as helping to cook being placed in the bedroom area rather than the kitchen area of the scene array). This research extends the findings of the Torralba et al. (2006) study by removing the context of the search items. This demonstrated that people will only look in the target associated areas when they are given the contextual information, such as the object's function, to guide their attention.

1.2.3 Templates and attentional set

There are times when the context of the search will guide attention, but only if the searcher knows exactly what they are looking for and where it is likely to be in a scene. However, in some applied visual search settings, the target item is visually unspecified (for example the monitoring of CCTV footage, security screenings, driving, or lifeguarding). This would mean that the event being monitored and the target being sought may take a number of different visual forms in relation to the context of the scene. Due to this level of uncertainty surrounding the target, errors in search processes can arise, with failures in detecting targets emerging from the ambiguity involved with having unknown numbers and types of targets that are often present in real world scenes (Hout & Goldinger, 2015; Schmidt & Zelinsky, 2009).

When targets objects are less specific, individuals tend to create an attentional set where they learn a set of features that are relevant to the task and tend to ignore features that are less relevant. There are times when attentional sets can override scene salience. In one example, Most and Astur (2007) show that attentional sets can affect individuals' ability to respond to unexpected and urgent information appearing in the real world. In a study where participants were required to follow either yellow or blue arrows in a driving simulation, they found that collision rates with a motorcycle that suddenly veers into the drivers path was substantially greater when the motorcycle did not match the colour of the drivers attentional set (coloured arrows showing directions). This goes against saliency hypotheses and shows the power attentional sets can wield over attention in visual scenes.

Research has also found that the type of cue used to shape attentional sets can affect the efficiency of target detection in real world searches (Schmidt & Zelinsky, 2009; Maxfield, Stalder & Zelinsky, 2014). In traditional visual search research, highly specified targets are optimal for guiding the searchers attention, creating the best attentional set. However, for targets that are less specified, such as those found in real world visual scenes, target detection can be more difficult. These searches are driven through imprecise information about the target, with searchers often using a non-specific target template (Hess et al., 2016; Maxfield et al., 2014). For example, in average everyday situations an individual would often engage in a number of scans of the environment, searching for specific items, in which they have seen before, such as an individual searching for their car in a crowed car park or their glasses in a cluttered room.

The individual would know what the target item they are seeking looks like, down to the specific details such as colour (Yang & Zelinsky, 2009).

However, more often in applied real world visual searches, scanning for a target item is more complicated, as targets are often not that specific, with individuals having to rely on general knowledge about the target to aid detection. For example, more complicated searches involve looking for a person in a crowd, a dangerous item in a suitcase scan or a distressed swimmer in a pool. In these more general searches, the individual conducting the search is aware of general features of the item or the underlying consistent outcome, but not the specific details, such as colours or general location (Schmidt & Zelinsky, 2009). Maxfield, Stadler and Zelinsky (2014) used written and verbal target templates for participants' searches of static images of real-world objects, finding that it is possible to guide searches with less-precise target templates. This enabled participants to learn specific features of the targets that allow them to discriminate targets from distractors

More specific target templates, such as visual templates are argued to be the best at guiding attention (Hess et al., 2016; Hout & Goldinger, 2015; Spotorno, Malcolm & Tatler, 2014). These templates are the most precise form of attentional set that one can have. For example, Schmidt and Zelinsky (2009) used target cues, such as a picture or written preview of the target, to measure the level of search guidance that cues provide. Five different types of cues were given: the most precise being a picture of the target and the least informative being an abstract text description (e.g. footwear). The other three target descriptions fell in-between the most and least informative. These were a precise text description with a colour feature of the target (e.g. brown boots), a precise description of the target (e.g. boots) and an abstract text description of the target with colour identity (e.g. brown footwear). One of the findings from this research was that as the amount of information in the cue increased, the search guidance improved. This was measured through eye fixations and saccades, and those targets that were cued with the most information were detected in shorter time frames, for example initial saccades to the target increased as more information was given in the target cue and distractor fixations decreased with more precise cue information.

In a more applied setting, target templates have been used in airport security screening training. This involved projecting target items (e.g. knifes, guns) onto real luggage scans in order to measure searchers ability to detect real threat items. In order to test the theory that searchers use category specific knowledge in real search situations, Smith et al. (2006) conducted a number of visual search screening tasks. One of the interesting results found was that when target items were selected from a library of pre-existing targets, participants were able to become familiar with the targets being used throughout the trials, and used this knowledge to identify targets for each subsequent trial, instead of applying general knowledge of what the target cold look like. However, one limitation of using category specific searches in this applied setting is that this training search method does not enable the searcher's cognitive capacity to be measured or aid with predictions about the searcher's ability to detect real threats. This is due to the evidence that suggests searchers learn to detect any potential targets that resemble those that have been used in tests, and thus searchers are applying a category-specific scan method and not a more flexible general search method for target items that may be dangerous but not resemble those used in the training.

1.3 Why are some searches less successful than others?

There are several factors that can aid or hinder the detection of a target in visual search. These include factors from both laboratory and applied real-world searches, particularly in areas such as driving, airport security and lifeguarding.

Although there are individuals who have been trained to spot and identify drowning swimmers, the detection of a drowning is a complex task due to a number of factors, such as the rare occurrence of drowning in swimming pools, complicated drowning behaviours or the pool environment (excessive heat, reflection, turbulence) (Lanagan-Leitzel et al., 2015). These factors can be related to visual search research that is well documented in the area of cognitive psychology, including factors such as target prevalence (Wolfe et al., 2005), similarities between search items (target-distractor similarities) (Feldmann-Wüstefeld & Schubö., 2014), and crowding (van den Berg, Cornelissen, & Roerdink, 2009). These factors could potentially play a negative role in the visual search of a lifeguard.

1.3.1 Target Prevalence

In typical laboratory visual search tasks, trials require searchers to discriminate between either target-present or target-absent tasks. While target-present trials assess the participant’s ability to search for a target item, the target-absent trials are often included as catch trials, providing a way to assess whether the participant is completing the experiment correctly. As a result, target-present trials typically make up 50% or more on a trial block. However, in real-world situations where visual search is required, target prevalence is much lower. For example, drowning is a rare occurrence for most lifeguards. Theoretical and applied real-world research has shown that targets which rarely appear can hinder the searcher's ability to detect targets in subsequent trials (Eckstein, 2011; Wolfe, Horowitz & Kenner, 2005).

The theory behind the prevalence effect suggests that searchers have an adjustable threshold for quitting searches where no target has been found, with searchers being more likely to quit if a target has low prevalence. Thus, if a target has high prevalence the searcher is willing to spend longer on target absent trials as previous experience would suggest that an early rejection could lead to a target being missed. Comparatively with trials where target prevalence is low, searchers are more likely to give up, as searching for longer periods of time has not led to successful results previously. Reaction time data has shown that searchers have faster detection rates after successfully identifying the target, but reactions comparatively slow down after any mistakes have been made as the searcher is likely to alter the time they spend looking for the target to avoid subsequent target misses (Wolfe et al., 2005).

Searches for high-prevalent targets often lead to more correct responses in comparison to searches that have low-prevalent targets. Wolfe et al. (2005) conducted an experiment using stimuli to represent airport security screening images. Target prevalence for the target items were 1%, 10% or 50%. The results for the 50% prevalence target showed an error rate of 7%. However, this error rate was seen to increase at both 10% and 1% prevalence, with 16% and 30% error rate respectively. Errors were reported as missed targets, which were target items that were failed to be detected. With the higher thresholds for low-prevalent targets, searchers are more biased to making target-absent responses due to the experience of trials, and this results in searchers failing to detect rare targets. In applied settings this low-prevalence effect could be seen to have devastating consequences, if targets are being missed due to the rarity of their occurrence. For instance, in lifeguarding there is a high potential for drowning victims to be missed with a higher threshold for drowning detection due to rare prevalence of actual drowning incidents.

1.3.2 Target-distractor similarity

One factor that increases the complexity of visual search (for instance, that of lifeguarding surveillance) is the similarity between the target and the distractor items. When search objects share similar features, searchers take longer to detect the target item (DeMers & Giles, 2011). In application to lifeguarding it can often be seen in fun swimming sessions that play behaviours can easily be confused with actual drowning behaviours. For example an individual doing the colloquially termed 'dead-man's float' looks the same as a surface-based, passive drowner, while the splashing and 'bobbing' of someone messing around in the water could be mistaken for behaviour associated with active drowning (Fenner et al., 1999).

An early theory of target and distractor homogeneity and heterogeneity in visual search proposes that distractor items that are similar in their features are grouped together and processed as a single unit, which acts as a tool for increasing search efficiency (Duncan & Humphreys, 1989). Showing the effects of distractor homogeneity on contextual cueing, Feldmann-Wüstefeld & Schubö (2014) found that distractors sharing similar features created a more pronounced effect of contextual cueing, with distractors that all shared the same orientation producing more efficient searches, (where distractors were rotated Ls and the target a T). The increased performance in the search was concluded to be due the homogeneous distractors being grouped together to create quicker decisions to disregard distractors and guide search to the target item. Processing items as a larger group also lead to more efficient representations in working memory, which heightened contextual cueing for trials that had been repeatedly presented. Therefore, search speeds are decreased not only with targets that are sufficiently different from the distractors, but also when distractors are all similar in their features.

When there are similarities between targets and distractors in visual search tasks, a slower target detection in noted, particularly compared to searches where a target is sufficiently different from the distractor items (Duncan & Humphreys, 1989). In application to real world search items, Alexander & Zelinsky (2012) used teddy bear stimuli to assess effects of target-distractor similarity, manipulating the features of distractor bears to match those of the target bear, for example, changing the legs of the distractor bear to match those of the target bear. This manipulation resulted in participants' reaction times being degraded for tasks in which distractor bears shared 1, 2, or 3 parts out of 4 with the target bear, with the greatest difficulty seen with those distractor bears that shared 3 parts with the target bear. With similar targets and distractors more false-positive responses to trials were reported compared to target bears that were missed, which would be expected for distractors that share maximum properties with targets, as features can be easily confused. Fixations for targets were also affected as the similarity between target and distractors increased, with longer verification times for target bears and more distractor bears fixated before the target bear. Thus, the guiding features of search become weaker as the salience of the target decreases and begins to blend in with distractor items.

Similarlity of targets and distractors across different trials has also been found to affect visual search outcomes. Smith et al. (2005) found that searchers created target image categories based on the items that had appeared in previous trials. However, targets were more likely to be missed when they were dissimilar from previous trials and from the specific target categories that searchers had created. This result was seen in the reduced reaction times for target similarity over repeated trials, with slower responses to targets that were dissimilar to those in previous trials. The effect of target and distractor similarity across different contexts has been also explored. Guest and Lamberts (2011) suggest that target and distractor similarity is not static, but a dynamic concept that changes depending on the information available at the time and as more perceptual information is accumulated. Therefore, accuracy of target identification is based on people making decisions about how similar the target item is to the other items in the display, and target identification is faster when distractor items share similar features.

1.3.3 Multiple target search and dual target costs

The inclusion of multiple targets in a search can potentially have a detrimental impact on the detection rates of the additional targets. There is a body of evidence that suggests once searchers have successfully identified a target item, that searcher is less likely to find a second target in the same scene, causing search failures (Cain et al., 2011). There is a problem with 'success breeding failure' in multiple-target visual search (Mitroff et al., 2015), which becomes apparent in applied situations where multiple targets might be highly unlikely, but potentially devastating, such as those in airport security screening, medical examinations or lifeguarding (Wolfe et al., 2013; Godwin et al., 2010; Lanagan-leitzel et al.,2015). In lifeguarding, additional (non-drowning) target behaviours alongside those of drowning and distress also add to the complexity of lifeguard visual search. Lifeguards must not only must they keep alert for drowning swimmers but they must also be attentive to risk-taking behaviours, rule breaking, and features of the pool such as the quality of the water (i.e. their attentional set for behavioural characteristics is not just limited to drowning behaviours).

This failure to find a second target, once a first has been detected, has been well documented in areas of applied psychology, and multiple search failure has been linked to the theory of the satisfaction of search (SOS). This theory claims that a specific target is more likely to be undetected by the searcher when there are additional targets, compared to when it is presented as a lone target (Tuddenham, 1962). Also, it is believed that once a target has been detected the searcher becomes satisfied with the meaning of the search, terminating any further search of the scene (Cain et al., 2011).

However, there is substantial evidence that suggests the satisfaction of search theory is not the only factor in failed multiple-target searches (Cain, Adamo & Mitroff, 2013; Biggs & Mitroff, 2014; Mitroff et al., 2015). Research from Mitroff et al. (2015) has proposed the alternate theory of subsequent search misses (SSM). This theory proposes that searchers continue their search even though they have become satisfied that they have found all targets. This would suggest that the satisfaction of finding the target is not enough to terminate a search, thus missed targets are not solely due to idea of search satisfaction, and other factors have a part in these failures. Some of these factors include the frequency of differing targets, different target types, the searcher's expectation for the number of targets present in the scene, and the external pressures searchers experience, such as the time the search takes and any rewards for finding target items (Fleck, Samei & Mitroff, 2010; Mitroff et al., 2015). Additionally, detection of secondary targets may be influenced by the *perceptual set account* and *resource depletion account* (Mitroff et al., 2015). The definition of the *perceptual set account* (Berbaum et al., 1991) suggests that the features of the first target biases the continued search for additional targets. In terms of the subsequent search in the same trial, any further targets would be sought based on similar properties to the first target, for instance, colour, shape, orientation or target relationship. Therefore, any targets that do not match these specific features may be missed. The definition of the *depleted resources account* (Cain & Mitroff, 2013) suggests that once a first target has been identified, an individual has limited cognitive functions available for subsequent searches of the same scene, due to the searcher storing features of the first target in the working memory.

In searches for multiple targets, it has been found that searchers make more errors, either through targets being missed or through-false alarm responses. In accurate response trials, reactions speeds were slower when multiple targets were presented compared to the single target searches. Furthermore, participants had to make more eye fixations to detect the target in multiple-target trials (Hout & Goldinger, 2010). The results of one particular study that used eye tracking technology suggest that dual target satisfaction of search (SOS) errors are a result of a number of factors, including errors in scanning where second targets were not detected or fixated, and errors in the decision process, where second targets are detected through fixations, but are not reported by the searcher (Cain et al., 2013). These types of errors possibly highlight a '*looked but failed to see'* error, particularly for these second targets that are fixated but not detected.

In application to lifeguarding, a related problem is termination of search due to the detection of a task-relevant (but non-drowning) target: if a lifeguard identifies swimmers engaging in risk-taking behaviours, they would need to interrupt their scan of the pool to intervene and stop the risk taking behaviour (Lanagan-Leitzel et al., 2015), thus potentially missing a drowning target. As rule-breaking and risk-taking are more prevalent targets than drowning incidents, there is also the problem that expectations may lower the threshold for detecting these common events at the expense of detecting swimmers in trouble. There is also the further issue with lifeguards focussing solely on these behaviours, due to them being more prevalent and taking up more of their attention meaning any subsequent drowning targets could be missed.

1.3.4 Crowding in visual search

Crowding in visual search is defined as an effect that limits the visual perception of different features of target objects when they are surrounded by a number of distractor items, resulting in visual search performance being dramatically reduced in terms of the searcher's ability to recognize and respond to crowded targets (Whitney & Levi, 2011). There is considerable overlap between crowding and the related concept of *visual clutter,* with both having a negative impact on visual search (van den Berg et al., 2009). As the number of items in a search area increases, the space between items becomes smaller and this limits the searchers attention to smaller areas of the search array (Pelli & Tilliman, 2008). This problem of visual clutter has been noted in other research studies, both in the laboratory and in applied settings. For example, Neider and Zelinsky (2011) found in visual searches of rural and urban scenes that individuals were better at detecting targets in rural scenes with limited clutter, compared to urban city scenes with high rates of visual clutter (wide open space, with minimal signage and traffic lights compared to urban closed spaces with lots of buildings, road signs and traffic lights). Furthermore, Ho et al. (2001) found similar effects in young and old people in their visual searches of roads, with more clutter in the search area having a detrimental effect on searches of road signs.

This phenomenon of crowding has applications to lifeguarding surveillance. For example, with increased numbers of swimmers, physical space within a lifeguard's supervision zone will become visually cluttered, which may result in delayed reaction times to drowning targets in their scan of the pool, as distractor swimmers will reduce the efficiency with which a target can be processed (Lanagan-Leitzel et al., 2015). Similarly, Griffiths (2002) reported that with increased numbers of swimmers in the pool, lifeguard surveillance performance decreased with any drowning swimmers becoming harder to spot as the pool space becomes crowded. In a pool setting, crowding is inevitably confounded with the number of distractors, though the effect of crowding is distinct from this, and is likely due to the need to have a tighter attentional focus when processing a foveated target.

When in crowded environments, targets that are typically easy to identify when presented in isolation, become difficult to distinguish from other distractor items (Whitney & Levi, 2011). Crowding effects have been explored in low-level feature stimuli with simple visual features, such as orientated lines, objects and faces (Manassi et al., 2012; Manassi & Whitney, 2018; Sun & Balas, 2015). However, recent research has begun to demonstrate crowding effects in high-level feature stimuli, including complex dynamic configurations. Louie et al. (2007) found that target distractor similarity has additional crowding effects. When upright flankers crowd holistic target faces, face recognition was strongly impaired. However, recognition impairment was shown to be weaker when inverted flanker faces crowded the target face. In a dynamic visual task, Ikeda and Watanabe (2016) found that crowding effects were stronger in tasks were targets and flankers were performing the same motion. Similar effects were found in a study by Ikeda, Watanabe, and Cavanagh (2013), who found that direction discrimination of a central moving target was effected more when the distance of the flanker stimuli was smaller, creating a crowding effect which resulted in participants reporting a direction that pooled the central target and flanker targets directions. They also found that a crowding effect was not seen when the flanker stimuli resembled a dotted outline of the central stimuli. In terms of lifeguarding, it may be possible that a crowding effect would influence drowning detection when the space between swimmers is smaller and swimmers are performing movements that are similar to drowning characteristics.

1.3.5 Dynamic visual search tasks

Unlike the numerous laboratory studies that assess an individual's search skills and processing speeds, visual search of the real world is rarely limited to static images as used in many studies (E.g. Godwin et al., 2015; Smith et al., 2005; Henderson et al., 2007; Meuter & Lacherez, 2016). In some applied settings the visual scene an individual would observe is dynamic, with moving targets and distractors, such as those in driving or lifeguarding (Chapman, Underwood & Roberts, 2002; Lanagan-Leitzel et al., 2015). These types of searches are more complex and have a certain level of difficulty. Factors that add to the complexity of searches include the possibility of occlusion of moving targets, complex motion, or changes in scene context as searchers' attention is focused on a different area. Not only do dynamic scenes cause problems for detection errors, there are issues that surround the perception of the moving scene. In static images the general 'gist' of the scene can be gauged effectively in very little time (on average 100ms), whereas the perception of dynamic scenes seems to encounter a lag between eye movement fixations and semantic processing (Howard, Troscianko & Gilchrist, 2010).

For moving stimuli in real-world applications, such as those in a recent study of suspicious behaviour in CCTV monitoring (Howard et al., 2013), continuous judgements and semantic processing are required to gather information about the scene and the potential target. Due to needing constant judgement of the moving visual scene, updated representations of the stimulus also need to be maintained. In dynamic real-world settings (e.g. lifeguarding) the potential target in the visual search of a scene does not take the form of a static image. Instead, targets are dynamic in nature and are rarely present from the start of a visual search.

Expertise in dynamic scenes has previously been explored, with evidence to suggest that individuals with certain domain experience will perform better in these complex tasks. For instance, Howard, Troscianko and Gilchrist (2010) have shown the effects of expertise in participant's responses to a video of a football match where participants were asked to continuously rate the likelihood of a goal being scored. The results of this research show that 'experts' made earlier eye movements to target-relevant areas of the screen (the goal-relevant locations), than the non-expert. This provided them with earlier information on which to base their ratings. Experts using contextual knowledge to guide search of dynamic scenes to task-relevant areas has been also shown in research of CCTV operators. Howard et al. (2013) found expert CCTV operators had superior search compared to novices and this was shown through consistency in eye positions and greater consistency in judgements of suspicious behaviours between experienced operators.

There is also a possibility that the motion of stimuli captures attention. A number of studies have found that moving targets in an array of static distractors captures the attention of the searcher, with faster responses to these types of target compared to static targets in moving displays (Verghese & Pelli, 1992; Royden, Wolfe & Kempin, 2001). Targets and distractors that move at different speeds also affect target detection times, with fast moving targets in slow moving distractors receiving faster response times than slow moving targets in fast moving distractors (Ivry & Cohan, 1992). Abrupt changes in target motion have also been demonstrated to affect search outcomes (Howard & Holcome, 2010). To understand the effects of movement in real-world search, Kunar and Watson (2011) explored visual search performance in highly complex scenes for moving, static and blinking search objects in high set sizes (16, 24, 32 objects). Error rates were found to be higher in this complex setting. The search for moving items was less efficient than search for static items, with targets being missed. However, this error rate was seen to decrease when target templates were given. In terms of lifeguarding, there are a number of different target behaviours to be wary of (active and passive drowning, rule breaking behaviours), and while knowing the exact template of these behaviour may improve search, the movement in this highly complex environment may potentially affect the number of drowning events detected.

1.4 Factors that influence expert visual search

Within the applied visual search literature, there is a large body of evidence suggesting the advantages of experience in visual search performance. For example, expert drivers are argued to have greater visual processing skills than novice drivers, experienced chess players show advantages over novice players, and airport security screeners use context for better search outcomes over non-professionals (Underwood et al., 2002, Reingold et al., 2001, Biggs & Mitroff, 2014).

Experiential advantages in visual search may be a result of repeated exposure to the same environments and search items in meaningful situations. One theory is that hundreds of hours of deliberate practice can make an individual proficient at a certain skill, including applied visual search (Ericsson, Krampe, & Tesch-Römer, 1993). Thus, the more practice someone has at something, the greater their ability is to perform that skill. For visual search skills, the advantage of hundreds of hours of practice is the exposure and experience with the task and related objects. For example, Evans et al. (2011) found that expert radiologists and cytologists have a greater memory for search images in their specialised domain, which they have spent a significant amount of time studying.

Although deliberate practice plays an influential role in shaping expertise, recent literature has found that it only forms a small part of expert performance.

Macnamara, Hambrick & Oswald (2014) found the effects of practice only accounted for 26% of variance in expert performance. While practice may develop search skills, such as greater memory capacity for search items, other skills and abilities may also result in expertise in certain domains. For example, faster processing speeds, or knowledge of situations may lead to better visual searches.

1.4.1 Memory in search

Using semantic information over visual information may be one mechanism that underlies expert visual search performance. For example, Brockmole et al. (2008) found greater search benefits in expert chess players when exploring repeated chess boards of meaningful game play when compared to novice players' performance in a visual search task. However, when learning boards with randomly placed search items, the expert chess players' search performance was halved. This suggests that the experts are able to use the context of the meaningful chess boards to create mental representations of boards and use semantic memory to provide useful information to locate the targets, thus experts are able to use memory for visual context within the search to guide them to target items.

It is also important to note that one of the key debates to emerge in visual search literature is the extent to which memory contributes to successful visual searches (Horowitz & Wolfe, 2001, 2003; Körner & Gilchrist, 2007, Geyer, Von Mühlenen, & Müller, 2007). In one study, Peterson et al. (2001) found that there is memory for fixated locations, with eye-data showing the majority of re-visitations to items were to the target. If visual search had no memory, one might expect more items to be re-examined, however it appeared that only the items that had not been scrutinized enough on the first glance were revisited. Similarly, Solman and Smilek (2010) also demonstrate visual search performance is influenced by search items locations. In this study it was reported that repeated conditions, where targets appeared in the same location within a block, were much faster and more accurately than responses to a random condition, where the target location was generated randomly for each trial.

There is also a suggestion that while some searches use memory, other searches do not, which results in differing levels of search performance (Horowitz & Wolfe, 1998). Searches that use memory to guide attention away from items that have already been examined are classed as systematic searches. These types of organised searches result in improved search performance and are more efficient, with any given area in the search scene only being viewed once per scan (Wang, Lin, & Drury, 1997). In contrast, it has been suggested that random searches do not use memory for previously fixated items, which leads to a less organised search. Random search is a memoryless process where any area of the search array is just as likely to be viewed as another, no matter how many times it has been viewed previously (Nickles, Melloy & Gramopadhye 2003). In application to lifeguarding, the trained use of a systematic search should result in lifeguards being able to perform better searches, by following an organised path that can be re-created to be more efficient in later searches. Otherwise, random searches could lead to some swimmers being missed if they are not salient enough to draw the lifeguard's attention. The use of a systematic verses random search has been reflected in research conducted on Polish lifeguards. This study found that lifeguards failed to detect a simulated drowning on the bottom of the pool because they did not follow and maintain an organised and continuous scan pattern as they were trained to do so (Michniewicz et al., 2011). This raises the question of whether direct instruction can actually result in long-lasting training effects on visual search (Dewhurst & Crundall 2008).

1.4.2 Chunking

Although there is debate in the literature for memory influencing visual search, there is also evidence that working memory used during visual search is limited to a capacity of 12 items which can be tracked after initial examination (Peterson et al., 2001). However, it may be possible for a searcher to attend to more items in the search, by engaging methods such as spatial chunking (Peterson et al., 2007). This allows the searcher to focus on groups of items rather than each item individually. Spatial chunking theory suggests that items in a location, such as cars parked in a carpark, are grouped together in the spatial memory (Sargent et al., 2010), with items being associated with specific locations or other items nearby. Chunking items together allows more information to be stored in the working memory and a larger amount of relevant information to be extracted from the scene. Boot et al. (2004) suggested that viewers can tag a group of related items in a visual search array as having already been inspected, rather than tagging each individual item in the search. This saves the searcher using up memory capacity and reduces the probability of previously rejected locations being revisited within the search. In terms of domain expertise, it has been argued that experts within a domain have a greater ability to chunk items together in their search of a scene. For example, Helsen and Pauwels (1992) suggest that expert athletes (e.g. football players) use chunking to organise information about the visual scene, which results in better searches in terms of accuracy and response times to the target (the ball).

Chunking of items in the visual display is also argued to produce faster search for the target, with experts showing greater skill at using chunking. For example, Reingold et al. (2001) found that expert chess players would fixate in the spaces between playing pieces, suggesting they were attending to configurations of pieces, resulting in a larger span of attention and faster processing of the game pieces. Conversely, novice players tended to look at each individual chess piece, which lead to a slower search. However, the ability to use large spans in visual search was only beneficial to expert players when viewing meaningful game configurations, and not when the pieces appeared in random locations. Findlay (1982) has suggested that searchers often look at the 'centre of gravity' within a chunk, which often falls somewhere in between individual items in the chunk (e.g. when orienting towards a group containing one larger and one smaller object, the eyes would land closer to the 'heavier' object). For pool surveillance this may translate to lifeguards being able to detect changes in the search zone faster or result in faster detection of target items by looking at groups of swimmers. This may be particularly apparent for experienced lifeguards who may have developed a strategy that incorporates an increased visual span by looking strategically in open spaces between swimmers in the pool.

While chunking may help lifeguards store more information from the events happening in the pool and extract more information, there is a danger that a distressed swimmer may get lost in a group of people that have been chunked together and therefore missed. Considering this problematic factor, it could be suggested that chunking may not be as important as other search skills for the expert lifeguard. However, organised chunking may help in controlled swim sessions, such as lane swimming or swimming lessons. In lane swimming there tends to be organised lanes based on swimming speed, thus stronger and faster swimmers are grouped in one lane and weaker or slower swimmers in another. It may be possible to chunk stronger, faster swimmers as these have a lower likelihood of drowning. Similarly, in swimming lessons it may be possible to chunk children in the higher grades as these are the more advanced swimmers. While grouping objects on the basis of proximity is not necessarily an infallible method of chunking (see Baylis & Driver, 1989; Driver & Baylis, 1992 for examples of colour and movement being preferred over proximity for chunking), it is however still likely to be important in a pool setting.

This still could be a potential risky method of conducting searches of pools, if a drowning target does not stand out within their chunk. However, the expert lifeguard may be able to detect changes in one swimmer's behaviour, who is not behaving like the rest of the chunked group (e.g. a struggling swimmer in a group of fast swimmers). Target-distractor dissimilarity within a chunk, may result in a within-chunk parallel search. Indeed, this may be one of the benefits of chunking: turning a serial search of 40 swimmers into 5 parallel searches of 8 chunks.

1.4.3 Identification of the target

One potential advantage of being an expert in a certain domain during visual search is the ability to process search items faster in order to identify and locate the target item. Experience with particular targets lowers their thresholds for subsequent identification, allowing faster acceptance of these targets in the future, and reducing false-alarm responses to non-target items (Randel, Pugh & Reed, 1996; Borowsky & Oron-Gilad, 2013). For example, in a study comparing expert image analysts from the Royal Marines to novice image analysts, Curran et al. (2009) examined processing speeds of a flickering image that switched between the original image and an image that was slightly changed. The changed image was either the same image from a different perspective, the same image with a search item changed, or the same image with an item changed *and* from a different perspective. It was found from EEG recordings that experts had an early response in the brain occurring 100 milliseconds faster than novices after a changed image was presented. Furthermore, the experts visually searched complex images faster when stimuli relevant to their domain expertise were present, suggesting that familiarity with search items made the scene display easier to search. This ability in experts to detect changes early is important to lifeguards, where changes in the pool need to be monitored. For example, people getting in or out of the pool, someone disappearing to the bottom of the pool, or an individual's swimming behaviour changing.

Expertise and experience in certain domains can help improve visual processing of items in displays and scenes, with shorter fixations and scanning time with people who have a level of experience compared to novices. Konstantopoulos, Chapman and Crundall (2010) found that driving instructors appeared to have shorter processing times, with shorter fixations distributed across a wider area of the driving display, and broader scanning of the road compared to learner drivers. It appears that, with more experience in driving, attention can be moved more quickly and less processing time is needed. Furthermore, research has also demonstrated that expert radiologists made fewer fixations and had longer saccades than novices when viewing the same medical images (Bertram et al., 2016; Kundel & La Follette Jr, 1972). Gegenfurtner et al., (2011) have also noted that the effect of shorter and fewer fixations to targets made by experts is present across many different applied domains.

1.4.4 Situational awareness

Situation awareness refers to the ability to perceive the relevant objects within a scene, comprehend their relationship to one another and predict how the scene will develop (Endsley, 2015). Situation awareness is influenced by domain experience, as viewers may be more aware of the probabilities that certain visual cues may lead to specific outcomes (Endsley, 1995; Kass, Cole, & Stanny, 2007). This results in more extensive searches due to an awareness of potential hazards and searchers' can build a mental catalogue of events that are likely to occur in similar situations, allowing viewers to prioritise areas of the scene on the basis of what might happen next (Crundall, 2016). Following on from Torralba et al.'s (2006) *scene priors,* we could envision comparable *prediction priors*. These do not necessarily guide attention to where a target is, but where a target (e.g. a hazard) might shortly appear. For instance, Pradhan et al., (2005) found that expert drivers would look at the front edge of a parked high-sided vehicle as they drove past, in apparent anticipation of an emerging pedestrian. With more experience an expert is able to create a larger catalogue of events that could occur in driving situations, plus the expert searcher is able to develop an expectation of the likelihood of them occurring. Based on this, expert lifeguards may have better detection of drowning swimmers due to having a mental model of events that could appear and lead to hazardous situations compared to non-lifeguards impoverished models of events in swimming pools. Lifeguards with more experience may be able to apply previous experiences to detect swimmers who may be vulnerable in the water, and their experience may allow them to be more flexible in their scans, disregarding behaviours that are similar to drowning (e.g. splashing or swimming on the bottom of the pool).

Lifeguards have been shown to alter their search strategy to accommodate for changing environments of the swimming pool and different activities that may be taking place based on how they think events will develop or what will happen next within the pool. For instance, at certain times, the number of children in the swimming pool is likely to outweigh the number of adults and it has been found that lifeguards change their observation habits when there are increased numbers of children in the pool (Harrell, 1999). In these situations, lifeguards tend to observe and monitor the children in the pool more than the adults. In this study it was found that with more children in the swimming pool, the lifeguards increased their scanning performance in a positive response to the higher level of children swimming. However, it was also found that when the number of children outweighed the number of adults by a substantial amount, scanning performance decreased, with more of the lifeguards' attention placed upon rule breaking and risk behaviours rather than the search for drowning and distress behaviours, which may lead to some drowning incidents being subsequently missed.

1.4.5 Multiple object tracking (MOT) and sustained attention

The ability to sustain attention in highly demanding tasks could potentially lead to a superior search in experts. This ability to attend to search items for longer periods of time would particularly benefit the search in tracking multiple objects, such as the real-world scene of swimmers in a pool. MOT theory suggests that an individual is able to track a small number of moving objects during visual search by pre-attentively tagging each item, which allows each tagged item to be followed around the screen (Pylyshyn, 1998). For instance, this skill to track multiple objects for long periods is seen in athletes that play in team sports, where they are required to track a target item, such as a ball, and track the movements of other players to avoid making any collisions. In a study comparing professional athletes, amateur sportsman, and non-athletes, Faubert (2013) found that professional athletes performed more efficient searches in MOT tasks, a skill that is highly important to a domain where the search items are constantly moving. The professional athletes were also found to have faster information processing of the dynamic information in the search task and better skills for selective and sustained attention in the search.

This ability to sustain attention in highly demanding MOT tasks is apparent in laboratory tasks that aim to mimic real world scenes. Wolfe et al. (2007) suggested that in real world tracking tasks a searcher's attention to the task will be needed over a prolonged period of minutes and not seconds like in traditional laboratory tasks. In a study to measure multiple object tracking over a prolonged period of time, Wolfe et al., found that an individual can sustain tracking performance for up to 10 minutes, with dynamic objects moving in and out of focus with little apparent cost to the searcher attention. Feedback about tracking performance helped keep the searcher engaged to the task. In lifeguarding, swimmers are constantly moving around the pool and often moving in and out of the lifeguard's focus, therefore being able to track multiple objects and have these objects disappear and reappear with little effect on scanning could possibly be important to surveillance. Furthermore, lifeguards are often on duty for long periods of time, on average 20 - 30 minutes, therefore the expert lifeguard should be able to sustain attention to tracking and scanning swimmers in the pool for the whole duration.

1.5 Research on lifeguards' visual search skills

Lifeguard visual search is one domain in applied cognitive psychology that has received very little research focus. With limited research in this area, there is very little information that can inform training in pool surveillance. Current training procedures have been based largely on trial and error of previous training methods and lifesaving techniques (Hunsucker and Davison, 2008). This can be seen in the U.K. RLSS lifeguard qualification the training manual, which has limited reference to visual search with only 6 out of 240 pages dedicated to scanning the pool. Furthermore, within this U.K. qualification, there is currently no formal assessment in pool surveillance for drowning swimmers.

Early research into lifeguarding visual search skills has been limited in its ability to inform training practices. Grandjean (1990) assessed lifeguards using a red ball drill, in which a red ball is thrown into the pool at any given time and a lifeguard has an allotted time to locate it. Although lifeguards were successful in detecting the ball in the majority of cases, this study is fundamentally flawed as a training technique for lifeguarding drowning detection. The lifeguards were being trained to search for a brightly coloured object, which does not have any likeness to a real drowning victim. One of the main limitations in the applicability of this research as a training method for pool surveillance is that lifeguards may be encouraged to lookout for signs that they are about to be tested, rather than signs linked to distress and drowning.

Later research has been more successful in assessing lifeguard visual search skills, by employing more realistic vigilance drills. For example, a study reported by Brener and Oostman (2002) developed the idea behind the red ball drill by introducing a submerged manikin into the pool rather than a brightly coloured ball. This was done covertly, without the on-duty lifeguard knowing a drill was to occur. This test was repeated over 500 times with different lifeguards, with responses videotaped for later analysis. The researchers found that over 90% of lifeguards failed to notice the submerged manikin within the industry standard of 10 seconds (10/20 scanning method). Less than half of the lifeguards (43%) identified the manikin in less than 30 seconds. On average it took successful lifeguards 1 minute and 14 seconds to detect the submerged manikin, with 14% of lifeguards completely failing to detect the manikin with a 3-minute time limit. While motivation and distraction may have played a role in these poor results, it raises the question of whether the training the lifeguards received was adequate enough to provide the fundamental skills of visual search to detect victims in the complex environment.

One possible limitation of this submerged manikin test reported by Brener and Oostman is that the sudden appearance of a submerged drowning victim may not work for a lifeguard who is using situational awareness to guide their visual search of the pool. Situation awareness requires precursors to upcoming events. The appearance of the manikin might have been more realistic than the red ball in regard to the actual target, but it would not have been preceded by any precursor behaviour. This potentially explains the high error rates in Brener and Oostman's report.

Although there are some limitations to the manikin drop test, managers and trainers of American swimming pools have developed this vigilance experiment into an audit test, which can be used as a tool to test their lifeguards' surveillance skills. One notable study has considered the effectiveness of such audit tests on improving lifeguard surveillance. Schwebel et al. (2011) assessed lifeguards scanning behaviours before and after audit testing, investigating effects of such audits on surveillance and swimmer risk-taking behaviours. Lifeguards' scanning behaviours were examined through observations before and after the audit tests had taken place. They found that submerged manikin tests helped improve performance of the lifeguard surveillance of the pool. In post-audit observations of lifeguard behaviours, it was found that lifeguards were more likely to be focused in their scanning, reducing the number of times they became distracted by safety-irrelevant activities. It was also found that the audits had a positive effect of the swimmers, with them engaging with fewer risk-taking behaviours due to the observable increase in scanning behaviours displayed by the by the lifeguards. The lifeguards' improved behaviours included responding to the swimming behaviour more often and an increase in active head movements during the pool scan.

While early research tested lifeguard search skills with using aids in the pool (e.g the red ball test, the manikin drop) other research has considered using a planned theoretical intervention; teaching rather than testing. Schwebel, Lindsey and Simpson (2007) planned and gave interventions that aimed to re-educate lifeguards working during a busy summer period at an outdoor facility. The intervention used pre-intervention observations of lifeguard scanning to highlight where failures in their scanning were found. A second part of the intervention emphasised contextual knowledge of situations, activities and people, which are related to an increased risk of drowning. The final part of the intervention focused on the severity of drowning incidents and statistics of drownings that had happened during that year in other facilities. This was done to raise awareness of the importance of scanning and surveillance. It was found that after the short intervention lifeguards significantly improved their scanning behaviours. This improvement included looking at the pool more frequently, becoming distracted fewer times, and engaging in more visibly active scans of the pool. One interesting side-effect of training was that after the intervention the level of risk-taking behaviours in the pool decreased. It is possible that swimmers are much more likely to follow the rules when the lifeguards show more observable scanning behaviours.

Naturalistic studies of lifeguard surveillance have shown that manikin drop tests and training interventions improve observable behaviours in lifeguards, such as increased head movements. Hoewever, it would be interesting to see how target detection, such as detecting drowning swimmers, is influenced. This would be difficult to test in real-life environments, as drowning incidents occur too infrequently to record actual drowning detection behaviour. Instead we would have to infer that lifeguards would be more likely to detect a drowning based on surrogate measures such as head movements. Therefore, it may be possible to explore lifeguard surveillance either by measuring behavioural responses to videoed recordings of drowning incidents or by measuring the eye-movements of lifeguards in laboratory settings.

1.5.2 Exploring lifeguard visual search with video stimuli

Although previous research into applied visual search has found evidence for experience and practice effects on search performance, the evidence of this superior search in experts is mixed when considering lifeguard performance. For example, Lanagan-Leitzel (2012) recorded lifeguards', instructors', and non-lifeguards' verbal responses to critical events while watching twenty 2-minute-long video clips of outdoor swimming activity. The three groups differed in opinion on the events that should be monitored, with instructors identifying more critical events than lifeguards, though there was a lack of consistency in the prioritisation of search areas within the groups. This raises the question of whether lifeguard trainers are failing to pass on essential knowledge and information to the lifeguards, or if the lifeguards are failing to apply the knowledge that trainers are passing on.

Results from an observational study of drowning-incident videos have shown that lifeguards may in fact have a superior search. Avamidis, Butterly & Llewellyn (2009) found in an investigation of rescuer characteristics that although experienced lifeguards reacted to drownings quickly, identification of the drowning or distressed swimmer was considerably lower, with around 50% of lifeguards accurately identifying the emergency. While this study showed that detection in lifeguards was relativity low, the lifeguards were actually found to have superiority in their detection skills when compared to untrained bystanders. The untrained bystanders in most cases failed to recognise the emergencies, despite their being substantial outward behaviour indicating drowning and distress.

To understand the effects of training and experience in drowning detection searches, Lanagan-Leitzel and Moore (2010) compared three groups: experienced lifeguards, a group of non-trained naive participants, and a group of individuals who had been given short training on drowning behaviours and scanning. All participants were required to watch sixty 30-second video clips of swimmers in lake settings, while eye movements were recorded. In terms of fixations, it was concluded that lifeguards show a superior search of the whole visual scene, with shorter and more frequent fixations than trained and naïve participants. Results further showed that the experienced lifeguards monitored more critical events (no actual drowning or distress, but behaviours associated with it: e.g. splashing, submersion, weak swimming stroke) than both the trained and naive participants, but this was not to a level of significance. The qualified lifeguards' performance was not much better than the participants who received short training. Out of 150 critical events presented to participants over the entirety of the video clips, lifeguards only monitored 54%, which proved to be little better than the participants who had received short training (an average of 49.2% events detected) and did not reach conventional levels of statistical significance. This suggests that lifeguards are not scanning and detecting incidents as well as they potentially could be. A possible argument arises from this finding, which suggests the positive impact of training. With short instruction, such as the few minutes training Lanagan-Leitzel and Moore's participants received, individuals with no prior experience were able to detect critical events to a similar standard of experienced lifeguards. The study also found that the trained participants monitored more crucial events than the naive participants, which was suggested to show that some drowning incidents and events, crucial for lifeguards to monitor, are not salient enough to draw the attention. If the events were salient, the attention of the untrained participants would have been guided to the prevalent locations and the events would have been detected.

One study used computer-animated beach scenes to explore drowning detection, where 63 swimmers 'heads' placed equally across the screen. In this study, Page et al. (2011) found the detection rates between novice and experienced lifeguards differed significantly when they were given additional contextual information (e.g. the location of a riptide), with experienced lifeguards detecting

31.6% compared to novice lifeguards' detection rate of 16.7%. When no contextual information was provided (i.e. that there is a rip current in the area), overall detection rates dropped. Although in this condition experienced lifeguards were still superior in detection rates and were five times more likely to detect a drowning victim than the novices (0% and 19.2% respectively). Despite this finding of lifeguard superiority, low detection rates were reported for both novice and experienced lifeguards, on average 29% in biased conditions and 16% in non-biased conditions. For example, in the final 3.5 seconds, of the 5 second disappearance, 12 out of the 69 lifeguards tested fixated in the relevant section of the screen, but only 7 of these 12 detected the drowning victim.

The study of Page et al. (2011) could not identify how experienced lifeguards achieved higher detection rates, as eye movements showed that visual search patterns in both groups followed the same systematic gaze behaviour, using similar scanning patterns. Suggestions were made by Page et al., to offer explanations for the detection differences, including the advanced contextual knowledge of experienced lifeguards and differences in processing visual information.

A further issue raised in this study is the low detection rates of both the experienced and novice lifeguards. This low detection rate of both novice and experienced lifeguards could be related to the speed in which a victim submerged under the water, which was within 5 seconds with no visible signs of struggling, distress, or weakness. This is an unrealistic scenario for lifeguarding in a pool and may not correspond with the taught 10-second scanning method, or evidence that suggests a victim tends to struggle at the surface of the water for 20-60 seconds (Pia, 1974). Alternatively, the restricted representations of swimmers used in this study (all swimmers were represented by the same bobbing head) may have influenced performance.

With only 7 out of the 12 lifeguards that looked in the correct area of the screen detecting the drowning swimmer it could reflect a *looked but failed to see* error (Hill, 1980). This error has been well researched in the applied domain of driving (Clabaux et al., 2012; Herslund & Jørgensen, 2004; Underwood, Humphrey, & van Loon, 2011). Commonly, drivers who report a *looked but failed to see* error look at the other road user, but see them when it is too late (or not at all). These errors often result either in collisions happening in front or to the side of the car (Koustanai et al., 2008). This error seems to be more prominent in experienced drivers over novices (Crundall et al., 2012). It has been noted that when an individual undergoes a *looked but failed to see* error their cognitive resources are often engaged in another task, depleting abilities to place attention to secondary tasks, such as approaching a junction where a driver has multiple tasks (Casner & Schooler, 2015). It is also possible that a person's expectations on what they will see will bias their processing. For example, when a driver approaches a junction, they believe that looking down the road will either reveal a car or no car. However, in the absence of a car, the driver is more likely to believe in no-car than in a motorbike being present.

1.5.3 A new approach to assessing lifeguard skills

Lanagan-Leitzel & Moore (2010) used genuine footage of swimming but without any actual drowning events. Conversely, Page et al. (2011) did use 'simulated' drownings but in extremely artificial scenarios. Laxton and Crundall (2018) aimed to bridge the gap between the previous two studies, to investigate visual search to realistic drowning events within a more realistic environment than provided by Page et al., (2011), yet more controlled than that used by Lanagan-Leitzel & Moore (2010).

This study used video stimuli of regimented swimming, which goes across the width of the pool (see Figure 1). Videos had either 3, 6 or 9 swimmers (all actors) in the pool and this was spread evenly across the 45 clips included in the experiment. In two thirds of the clips a staged active or passive drowning would occur, while in the other third no drowning instances happened. The drowning events happened quasi-randomly within the second half of the video clips. The results showed that lifeguards were superior in both accuracy and speed of responses to these mock-drowning incidents. This study also considered the effects of different drowning types, finding that active drownings were responded to more accurately, but also received slower responses than passive drownings. At an intermediate set size, with six swimmers in the pool, drownings were responded to more slowly and less accurately, suggesting that, as the set size changes, the searcher alters their search strategy with varying levels of effectiveness. This research was not however without limitations. A false alarm response made before drowning onset in the Laxton and Crundall experiment ended the trial prematurely. Non-lifeguard participants were over-represented in their premature responses (17% vs. 7% for non-lifeguards and non-lifeguards respectively), raising the possibility that, if given the opportunity to see the full trial, the non-lifeguards may have performed similarly to the lifeguard participants in detecting actual drowning targets.

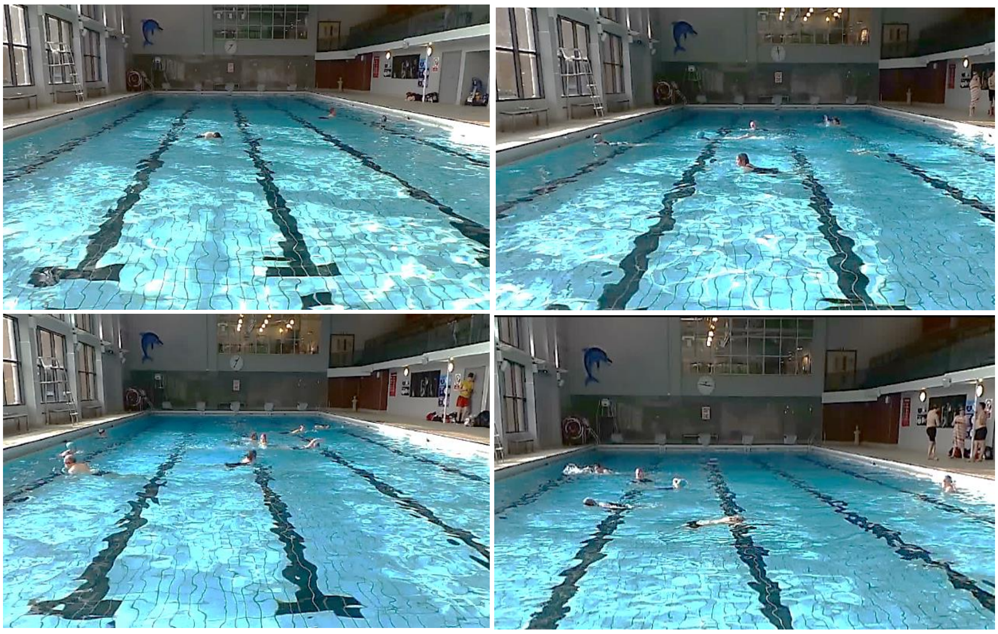


Figure 1. Four screens shots of the swimming pool stimuli from Laxton and Crundall (2018).

1.6 Rationale and Principle Aims of the Thesis

The scant research into lifeguard visual search has demonstrated advantages for lifeguard surveillance skills in detection of critical events and drowning incidents (Lanagan-Leitzel & Moore, 2010; Page et al., 2011). Recent research has shown that lifeguards are faster and more accurate in their responses to both active and passive drownings (Laxton & Crundall, 2018). Whilst numerous methods have been used to assess lifeguard drowning detection, these methods have presented a number of limitations, including impracticality (live-trials; Brener &

Oostman, 2002), low fidelity stimuli (Page et al., 2011), or problems with the study design (premature responses; Laxton & Crundall, 2018).

The limitations to previous research make applications to lifeguarding difficult. For example, highly controlled artificial displays making any findings hard to generalise back to pool or beach settings, or settings that lack experimental control, which makes it hard to conclude any results. To further assess if visual skills improve with lifeguarding experience, research should begin to consider the use of naturalistic and dynamic stimuli in laboratory conditions. This will allow for visual search skills to be tested in realistic conditions, while differences in experience are investigated. There has also been limited research exploring the cognitive skills that may underlie lifeguard visual search. If these were explored, then it may be possible to create a training tool based upon any underlying cognitive skills to improve overall lifeguard surveillance for the detection of drowning swimmers.

Consequently, the overall aim of the thesis is to explore the visual search skills of lifeguards in a naturalistic, dynamic search task, whilst exploring different conditions and to understand if these skills can be trained. This will be achieved by answering the following questions:

- Do visual skills improve with lifeguard experience?
- Are there any domain-free cognitive processes (e.g. multiple object tracking) that might underlie the superior visual skills of expert lifeguards?

- Can visual search be trained to improve new lifeguards' surveillance in swimming pools?

1.7 Structure of this Thesis

The second chapter of this thesis will give an overview of the general methods employed in the experimental chapters. This will cover the apparatus and detailed descriptions of the stimulus that was used commonly across experiments. Specific methods for each experiment (participant information, procedures) will be detailed within the experimental chapters, in the relevant sections.

The experiments in the first chapter (Chapter 3) aimed to replicate in part the original experimental findings from Laxton and Crundall (2018) of the superior responses of lifeguards to videoed footage of simulated drowning incidents when compared to non-lifeguards. Additionally, these detection rates were also compared across different drowning types (active and passive drownings) and array size (3, 6 or 9 swimmers in the pool) (Experiments 1 and 2). The first experiment also employed eye-tracking measures and the second experiment considered the effects of additional participant groups (lifesavers and lifeguard trainers, alongside the lifeguards and non-lifeguards). If lifeguards have superior detection of drowning and distressed swimmers, it would be expected that they would have faster and more accurate responses the drowning swimmers than non-lifeguards, but also fixate more of the drowning swimmers, with quicker first fixations to targets.

Chapter 4 reports lifeguard experience effects in a naturalistic test of drowning detection, with more realistic numbers of swimmers in the pool and of fun swimming compared to the regimented lap swimming of experimental Chapter 3. To assess this, real videoed footage of (active) drowning swimmers in a wave pool were obtained, which assessed reaction times and accuracy of responses (Experiment 3), and accuracy of responses in an occlusion task (Experiment 5). Eye-movement measures were also recorded alongside reaction time and accuracy data (Experiment 4). Real-world, dynamic search tasks are complex, however with lifeguard experience, it is expected that the superiority of lifeguard responses shown in Laxton and Crundall (2018) will be replicated, with lifeguards producing faster and more accurate responses than non-lifeguards to incidents of drowning and distress in these real clips.

Contributing cognitive mechanisms to lifeguard visual search were explored in Chapter 5. One experiment (Experiment 6) compared lifeguard and non-lifeguard performance of two cognitive tasks, the Multiple Object Avoidance task (MOA) and the Functional Field of View task (FFOV). A shortened version of the real drowning occlusion task was also employed. If these cognitive mechanisms play a role in lifeguard visual search in detection of a drowning swimmer, it is expected that lifeguards will have higher performance on these tasks, and that performance on the MOA and FFOV will be positively associated with performance on the shorted occlusion task.

The last experimental chapter (Chapter 6) reports the use of a perceptual processing training tool for drowning detection. It would be expected that an experimental group, that train on stimuli of drowning and distressed swimmers, will improve on their rates of accuracy from a pre-training drowning test to a post-training drowning detection test, compared to a control group, who train on stimuli of Flowrider surfers.

The final chapter (Chapter 7) will summarise the main findings from the thesis and explore the general conclusions that can be drawn from the experimental chapters. Limitations, future directions and original contribution to knowledge will also be discussed.

Chapter 2
General Methods

The exact methodologies that were used within this thesis vary across each experiment. Therefore, each experimental chapter will describe the methods used in more specific detail than will be outlined here. This chapter will focus upon detailing the apparatus that was common across experiments and providing a detailed description of the experimental stimuli and the methods used for collecting eye movement data.

2. Introduction

What methods are best to assess lifeguards' visual skill when searching for drowning swimmers? A number of methods have been used to explore lifeguard drowning detection in previous research, however these have a number of limitations, such as impracticality or poor-quality stimuli. One of these methods, which was used in early research for lifeguard drowning detection, is real-life tests (e.g. red ball drills, Grandjean, 1990; manikin drops, Brener & Oostman, 2002). These real-life tasks are impractical for the proposed research, as they present difficulties in measuring lifeguard responses and problems with introducing targets into the pool without the lifeguard's knowledge.

In other research, artificial stimuli have been used (Page et al., 2011). These artificial scenes portrayed impoverished graphics of swimmers in an ocean. One of the problems of using low-fidelity clips is that they lack realism, which makes it difficult to assess lifeguard visual skills and generalise findings back to real situations. There is currently no possibility to access good computer graphics to assess lifeguards' drowning detection for the proposed research, as no such content exists for swimming pool environments. Other applied domains have demonstrated the effectiveness of good quality computer graphics. For example, in driving research there are simulators to create CGI hazard clips which assess driving skills. However, to create bespoke hi-fidelity graphics for a swimming pool environment would be too costly for this project.

Static images of real-world scenes have also been used to explore visual search differences between experts and novices. Images of swimming pools would provide a hi-fidelity search environment for the proposed research. However, the dynamic nature of the search environment is a key challenge for lifeguards, which would not be represented in static image searches.

With the limitations to methods employed in previous research for assessing the visual skills of lifeguards, it was decided that staged and naturalistic drownings captured on video would provide the most realistic environment for assessing lifeguard visual skills. Therefore, this thesis employed videos of staged and real drowning incidents (see Figure 2 and section 2.1). Eye-tracking was chosen as a key methodology and variations on methods including an occlusion paradigm and the use of touch screen responses were also employed. All of these will be discussed in the following sections.

2.1 Experimental stimuli

A series of experiments were created to assess lifeguards' visual skills compared to non-lifeguards. Experiments 1-4 employed a reaction time drowning detection test, where participants were required to respond to a drowning incident in simulated and natural conditions (see Figure 2). Participant response times, accuracy, location accuracy and eye-movements were all recorded across these four experiments. Details of experimental stimuli can be found below.

Figure 2. Two screen shots taken from (left) the simulated drowning clips used in Experiments 1-2, and (right) the naturalistic video clips used in Experiments 3-5.

2.1.1 Simulated drowning video clips

In order to test drowning detection in Experiments 1 and 2, simulated drowning footage was filmed. Volunteers from a local lifesaving club were recruited to be actors for a filming session organised at a local swimming pool. As lifesavers are well practiced at simulating drownings for their own training purposes it was decided that these would be best suited for the requirements of the first two studies. Details of each video clip can be seen in Table 1.

On average drowning events lasted 10 seconds and were preceded by at least 20 seconds of normal swimming activity. However, drowning lengths were subject to the actors' ability to hold a drowning position. Actors were provided with a short whistle blast to indicate the start of the drowning event (no sound was included on the final clips, so this did not act as a cue in the studies). All actors, except one, volunteered to simulate drowning incidents and all willing actors performed at least one drowning event across 30 trials. Actors were instructed to swim laps across the width of the pool, and on cue, the target swimmer would begin to simulate drowning. Actors were instructed to either stop drowning after 10 seconds (a long whistle blast was sounded) or when they could no longer hold their breath. All actors were told not to look at the camera or instructor. Two-thirds of the videos displayed a staged active or passive drowning and the other one-third were catch trials with no drowning event. Catch trials were cut from a 3-minute video of swimming activity with no staged drownings.

Initial video footage was recorded on a Samsung Galaxy EK-GC110 23mm handheld digital camera, which was attached to a standard tripod positioned 1 metre from the edge of the pool and at an approximate height of 1.6 metres. The camera was pointed down the length of the pool, capturing the shallow end of a 25 by 15 metre pool, but also environmental features, such as the poolside equipment, windows with views into a gym corridor and a pool-side clock on the distant wall. Swimmers were placed in a 10m by 15m section of the pool, all within visibility of the camera, and asked to swim across the 15m width of the pool. The depth of the swimming area gradually declined from 1.2 metres to 1.8 metres (see Figure 3), with swimmers free to change position in this area if they wished to stand.

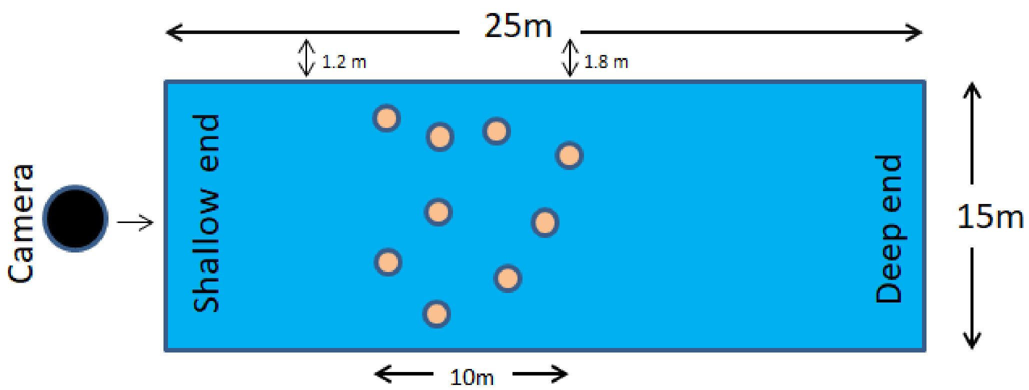


Figure 3. Graphic image displaying the position of the camera and the location of the swimmers (yellow circles) in relation to the size and depth of the pool.

Distractor swimmers were told to swim naturally, and a variety of strokes were used, which the actors were free to choose themselves. Swimming varied in pace and whether it was done above or below the surface. Some swimmers changed stroke after each lap, switching from a prone position to a supine position in the water. Pauses for natural behaviours were also permitted, such as taking a rest, talking with others, or altering goggles/swim hats, although these behaviours typically occurred at the sides of the pool.

In total, 9 actors were recruited, and trials were split evenly across 3, 6, or 9 swimmers. Clips were edited so that the onset of the drowning events did not all occur at the same time. A breakdown of these details can be seen in Table 1.

Video clips played in full, with reaction times being recorded for any correct responses that were made after the onset of drowning. In the eye-tracking experiment, participants were able to make multiple responses. More details of the study design can be found in the method section for each separate experiment in the following chapters.

Table 1. The features of drowning events in the experimental stimuli of Experiment 1 and 2.

Clip name	No. of swimmers	Length of clip (ms)	Drowning onset (ms)	Drowning window length (ms)	Drowning type	Description of the target
Clip 1	3	28000	17500	10500	Active	Centre-middle of the swimming pool, swimming breaststroke. Moving drowning towards the left
Clip 2	3	27000	18733	8267	Active	Middle of the pool at the right-hand poolside, swimming backstroke, but rolls onto front. Stationary drowning
Clip 3	3	29000	18300	10700	Active	Middle of the pool at the right-hand poolside, swimming frontcrawl. Stationary drowning
Clip 4	3	28000	8800	19200	Active	Centre-back of the pool, swimming frontcrawl. Stationary drowning
Clip 5	3	27000	16933	10067	Active	Back of pool at the right-hand poolside, swimming frontcrawl. Stationary drowning
Clip 6	3	29000	20600	8400	Passive	Centre-middle of the pool, swimming breaststroke. Drowner drifts towards the

						right
Clip 7	3	29000	20666	4334	Passive	Centre-middle of the pool, swimming breaststroke. Drowner drifts towards the right, starts underwater but rises to surface, ending at the right-hand poolside
Clip 8	3	29000	22266	6734	Passive	Back- left of the pool, swimming breaststroke away from the left-hand poolside. Stationary drowning
Clip 9	3	29000	19000	10000	Passive	Front of swimming area at the right-hand poolside, swimming doggy paddle. Stationary drowning
Clip10	3	28000	18166	9834	Passive	Centre-front of swimming area, push-off from right-hand poolside, underwater and floats to surface. Stationary drowning
Clip11	3	29000	-	-	No Drowning	-
Clip12	3	28000	-	-	No Drowning	-
Clip13	3	30000	-	-	No Drowning	-
Clip14	3	29000	-	-	No Drowning	-
Clip15	3	29000	-	-	No Drowning	-
Clip16	6	27000	16800	10200	Active	Front, centre-right of pool, swimming breaststroke towards right of pool. Stationary drowning
Clip17	6	29000	14433	14567	Active	Middle, centre-right of pool, swimming breaststroke towards right of pool. Drowner drifts towards the right-hand poolside
Clip18	6	29000	16633	12367	Active	Middle-left of the pool, moving away from the left-hand poolside towards the right. Stationary drowning
Clip19	6	29000	17200	11800	Active	Back, centre-right of pool, swimming frontcrawl towards left. Drowner drifts towards centre.
Clip20	6	29000	16033	12967	Active	Back, centre-left, swimming doggy paddle towards left

						of pool. Stationary drowning
Clip21	6	27000	14800	12200	Passive	Front, centre-right of pool, swimming breaststroke towards the left of pool. Stationary drowning
Clip22	6	29000	19933	9067	Passive	Middle, centre-right of pool, swimming frontcrawl towards right. Drowner drifts right towards right-hand poolside
Clip23	6	29000	21366	7634	Passive	Middle-centre of pool, swimming breaststroke towards left. Drowner drifts towards centre-left of pool
Clip24	6	29000	19400	9600	Passive	Middle, centre-right of pool, swimming breaststroke towards left. Drowner drifts towards centre of pool
Clip25	6	29000	18966	10034	Passive	Front-centre of pool, swimming breaststroke towards the right. Stationary drowning
Clip26	6	29000	-	-	No Drowning	-
Clip27	6	27000	-	-	No Drowning	-
Clip28	6	29000	-	-	No Drowning	-
Clip29	6	27000	-	-	No Drowning	-
Clip30	6	25000	-	-	No Drowning	-
Clip31	9	28000	16766	11234	Active	Front-centre of the pool, swimming breaststroke towards the left. Stationary drowning
Clip32	9	29000	16766	12234	Active	Middle-centre of the pool, swimming breaststroke towards the left. Drowner drifts towards the left-centre
Clip33	9	29000	13766	15234	Active	Middle, centre right, swimming frontcrawl towards the right. Stationary drowning
Clip34	9	29000	14466	14234	Active	Back-centre of the pool, swimming doggy paddle towards the right. Stationary drowning

Clip35	9	31000	11800	19200	Active	Middle, centre right, swimming frontcrawl towards the left. Stationary drowning
Clip36	9	29000	17633	11367	Passive	Middle-centre of the pool, swimming frontcrawl towards the left. Drifts towards centre-left
Clip37	9	29000	20300	8700	Passive	Middle, centre-left of pool, swimming breaststroke towards the left. Drifts towards left-hand poolside
Clip38	9	29000	17866	11134	Passive	Front-centre of pool, swimming breaststroke towards left. Slight drift towards centre left
Clip39	9	29000	19666	9334	Passive	Middle, centre-left, swimming frontcrawl towards the left. Stationary drowning
Clip40	9	21000	9600	11400	Passive	Back, left-hand poolside, swimming frontcrawl towards the left. Stationary drowning
Clip41	9	27000	-	-	No Drowning	-
Clip42	9	29000	-	-	No Drowning	-
Clip43	9	29000	-	-	No Drowning	-
Clip44	9	29000	-	-	No Drowning	-
Clip45	9	29000	-	-	No Drowning	-

2.1.2 Real drowning video clips

Chapter 4 employed real footage of drowning and distress to explore any differences between lifeguard and non-lifeguard drowning detection. Initial video footage for this experimental chapter was accessed from YouTube with the uploader's permission to use for experimental stimuli[1]. Wavepool lifeguard rescue videos 1-42 were used in the experiment. The drowning incidents were

[1] Footage can be found at https://www.youtube.com/channel/UCnERyC7dwJwTvEyzYz6uxHw.

captured on CCTV footage from an American wave pool. Footage is completely naturalistic, with swimmers (mostly children) engaging in fun swim behaviour (e.g. chatting in a group with friends, riding on inflatable rings, swimming and playing). The drowning incidents are real swimmers in distress; however, all video clips have a real lifeguard performing a rescue in a timely manner (within the taught 10:20 second standard) and none of the rescued swimmers suffered any long term injury or distress from the incident.

The clips were edited to vary in length, ranging between 9-35 seconds. Drownings occurred pseudo-randomly within the trial after the first 5 seconds. The drowning incident clips were cut at the point in which the real pool lifeguard makes their response and enters the water (i.e. before the appearance of the lifeguard). The drowning incidents lasted between 2-19 seconds with clips ending immediately following the drowning. The pool's wave machine is in action for some of the drowning events. A breakdown of trials can be seen in Table 2.

If a correct response was made the video clip would terminate and the next clip would automatically start. If no correct responses were recorded the video clips would play in full. Response times and location accuracy were recorded. More details of the study design are outlined in the methods section before each separate experiment in the following chapters.

Table 2. The features of the video footage used in the experimental stimuli of Experiment 3 and 4.

Clip name	No. of swimmers	Cut from original clip (start time) (sec)	New clip length (sec)	Drowning onset (sec)	Drowning window length (sec)	Zoom (%)	Description
Wavepool rescue 1	49	15.09	22.28	15.02	7.26	-	Near to the camera. Swimmer falls from rubber ring
Wavepool rescue 2	61	13.09	23.13	15.03	8.10	-	Near to the camera. Swimmer lets go of rubber ring in deep end of pool
Wavepool rescue 3	79	39.17	22.52	10.02	12.50	-	Near to the camera. Rubber ring flips over with small child on top.
Wavepool rescue 4	30	11.09	23.23	17.11	6.12	-	Near the camera. Swimmer falls from rubber ring and tries to swim frontcrawl.
Wavepool rescue 6	40	0	15.15	6.24	8.81	-	Near the camera. Swimmer falls from rubber ring.
Wavepool rescue 8	39	13.04	23.16	16.09	7.07	-	Near to the camera. Swimmer falls from rubber ring.
Wavepool rescue 9	30	0	20.11	16.20	3.91	-	Near to the camera. Swimmer lets go of rubber ring.
Wavepool rescue 13	62	18.17	25.07	12.19	12.88	-	Near to the camera. Swimmer tries to move from rubber ring.
Wavepool rescue 15	51	4.04	35.08	16.17	18.91	-	Far from camera. Swimmer struggling in wave machine.
Wavepool rescue 16	35	0	17.05	11.12	5.93	115	Far from camera. Swimmer surface dives out from under a rubber

							ring in deep end.
Wavepool rescue 18	49	0	23.12	18.04	5.08	105	Far from camera. Swimmer lets go of rubber ring
Wavepool rescue 19	23	34.17	22.52	20.15	1.99	110	Near camera. Swimmer falls from rubber ring, then swims frontcrawl for 15 seconds and then begins to drown
Wavepool rescue 20	45	0	29.06	14.23	14.83	-	Near to camera. Swimmer surface dives out from rubber ring in deep end of pool
Wavepool rescue 21	23	6.20	32.28	13.26	19.02	108	Far from camera. Swimmer lets go of rubber ring during wave machine.
Wavepool rescue 22	25	0	18.09	7.03	11.06	-	Near to camera. Swimmer surface dives out from rubber ring in deep end of pool
Wavepool rescue 23	77	7.12	25.18	22.04	3.14	-	Near to camera. Swims breaststroke away from rubber ring in deep end, cannot stand up
Wavepool rescue 24	83	0	15.06	11.22	3.84	-	Far from camera. Sat on rubber ring and falls off
Wavepool rescue 25	46	0	21.10	16.28	4.82	115	Far from camera. Swimmer inside rubber ring and ring flips.
Wavepool rescue 26	83	12.14	32.25	23.19	9.06	120	Far from camera. Swimmer surface dives out from rubber ring.
Wavepool rescue 27	89	0	12.12	9.17	2.95	120	Near to camera. Swimmer sat on top of rubber ring and ring flips
Wavepool rescue 28	50	0	26.16	21.24	4.92	115	Near to camera. Swimmer sat on top of rubber ring and ring flips

Wavepool rescue 32	47	0	18.14	13.04	5.10	115	Far from camera. Swimmer sat on top of rubber ring and ring flips over
Wavepool rescue 34	75	0	29.00	23.21	5.79	125	Far from camera. Swimmer surface dives from inside a rubber ring
Wavepool rescue 35	60	0	25.17	16.17	9.00	120	Far from camera. Swimmer is struggling in wave machine
Wavepool rescue 37	67	0	18.10	13.22	4.88	125	Far from camera. Swimmer laying on rubber ring, slides of
Wavepool rescue 38	40	33.15	9.1	5.28	3.82	125	Far from camera. Swimmer sat on rubber ring, falls off
Wavepool rescue 39	36	0	15.28	10.05	5.23	125	Far from camera. Swimmer sat on top of rubber ring. Ring flips
Wavepool rescue 40	28	0	33.04	26.12	6.92	120	Near camera. Swimming doggy paddle towards deep water, tries to grab loose lane rope
Wavepool rescue 41	27	0	11.26	7.23	4.03	125	Far from camera. Swimmer sat on top of rubber ring, leans forward and falls
Wavepool rescue 42	34	0	19.18	16.00	3.18	120	Far from camera. Moves towards deep water and cannot stand up
Wavepool rescue 1 catch	51	-	16.00	-	-	-	No drowning
Wavepool rescue 2 catch	34	-	14.30	-	-	-	No drowning
Wavepool rescue 3 catch	58	-	15.17	-	-	-	No drowning
Wavepool rescue 4 catch	21	-	10.24	-	-	-	No drowning

Wavepool rescue 5 catch	42	-	12.00	-	-	-	No drowning
Wavepool rescue 8 catch	46	-	11.56	-	-	-	No drowning
Wavepool rescue 10 catch	35	-	9.07	-	-	-	No drowning
Wavepool rescue 12 catch	33	-	11.02	-	-	-	No drowning
Wavepool rescue 13 catch	39	-	16.43	-	-	-	No drowning
Wavepool rescue 17 catch	63	-	15.11	-	-	110	No drowning
Wavepool rescue 19 catch	29	-	17.06	-	-	110	No drowning
Wavepool rescue 29 catch	53	-	9.40	-	-	110	No drowning
Wavepool rescue 32 catch	43	-	12.14	-	-	115	No drowning
Wavepool rescue 34 catch	70	-	16.07	-	-	125	No drowning
Wavepool rescue 42 catch	24	-	9.10	-	-	120	No drowning

Wavepool rescue videos 1, 2, 4, 13, 15, and 22 were filmed from a stationary camera, which was zoomed in on the deep end of the pool. No side features of the pool were captured.

Wavepool, rescue videos 3, 6, 8, 9, 19, 20, 23, and 24 were filmed from a stationary camera placed in the left corner of the pool, looking down from the deep end of the pool towards the shallow end. The sides of the pool were not filmed in these clips.

Wavepool rescue videos 16, 18, 21, 25, 26, 27, 28, 32, 34, 35, 37, 38, 39, 40, 41, and 42 were filmed from a stationary camera placed in the left corner of the pool, looking down the pool from the deep end to the shallow. The camera had a view of the poolside lifeguards stationed in the deep end. These clips were edited in Adobe Premiere Pro, zooming in on the video to cut out the view of the poolside activity, but keeping the view of the deep end down to the shallow. The percentage of zoom can be seen in Table 2.

Catch trials were cut from the same wave pool rescue clips as the drowning trials. Wavepool rescue videos 1, 2, 4, 8, 12, and 13 were filmed from a stationary camera, which was zoomed in on the deep end of the pool. Clips 3, 5 and 10 were filmed from a stationary camera in the left corner of the pool, looking down the pool from the deep end to the shallow, with not poolside features captured. Clips 17, 19, 29, 32, 34, and 42 were filmed film from a camera stationed in the left deep end corner looking down the pool towards the shallow end, with some poolside features captured. These clips were edited and zoomed in to crop out the poolside view.

2.1.3 Dynamic Touch Screen Stimuli

Experiments 2 and 3 required participants to make localised responses on a touch screen laptop. In order to create a responsive area of the screen, which is defined by coordinates and encompasses the drowning target (a response window), a number of procedures were followed using python coding in Psychopy. First, a test was created to gain the central coordinates of each drowning swimmer from the start of drowning onset. The centre of the screen was coded as the [0,0] point of an axis and drowning coordinates were recorded from a mouse click and saved into a txt save file.

A second test was then created to assess the movement of drowning swimmers who drifted from the drowning onset position. A visible responsive window was placed around each drowning swimmer, which assessed if the drowning target drifted. The speed of drowning swimmers' drift was calculated in pixels across the x-axis, which created a responsive window that moved with any drifting targets. Minus numbers were used to code the pixels for responses window around drowning swimmers who drifted to the left and positive numbers were used for swimmers who drifted to the right. Details of this can be seen in Table 3 for Experiment 2 and Table 4 for Experiment 3.

Table 3. Location and drifting speed of drowning swimmer for Experiment 2

Clip name	Location [x,y]	Do they drift?	Drifting speed (pixels)
Clip 1	[106,108]	Yes	-0.3
Clip 2	[345,108]	No	0
Clip 3	[309,79]	No	0
Clip 4	[105,116]	Yes	-0.1
Clip 5	[212,115]	No	0
Clip 6	[118,92]	Yes	0.05
Clip7	[205,89]	Yes	0.2
Clip 8	[-149,114]	No	0
Clip 9	[437,57]	No	0
Clip 10	[-98,58]	No	0
Clip 16	[240,42]	No	0
Clip 17	[125,96]	Yes	0.2
Clip 18	[-225,107]	No	0
Clip 19	[111,118]	Yes	-0.09
Clip 20	[-115,112]	Yes	-0.1
Clip21	[253,58]	No	0
Clip22	[132,74]	Yes	0.2
Clip23	[11,87]	Yes	-0.3
Clip24	[92,88]	Yes	-0.3
Clip25	[-95,31]	Yes	0.2
Clip 31	[8,62]	Yes	-0.08
Clip 32	[-50,91]	Yes	-0.1

Clip 33	[140,86]	Yes	0.1
Clip 34	[-54,126]	No	0
Clip35	[189,93]	Yes	-0.15
Clip 36	[-52,69]	Yes	-0.3
Clip 37	[-148,72]	Yes	-0.4
Clip 38	[-10,43]	Yes	-0.3
Clip 39	[-103,61]	Yes	-0.1
Clip 40	[-225,113]	No	0

Table 4. Location and drifting speed of drowning swimmer for Experiment 5

Clip name	Location [x,y]	Do they drift?	Drifting speed (pixels)
Wavepool rescue 1	[408,4]	No	0
Wavepool rescue 2	[465,279]	No	0
Wavepool rescue 3	[214,29]	No	0
Wavepool rescue 4	[379,22]	Yes	-0.1
Wavepool rescue 6	[540,103]	No	0
Wavepool rescue 8	[-189,-128]	No	0
Wavepool rescue 9	[-270,-15]	No	0
Wavepool rescue 13	[-50,71]	Yes	-0.1
Wavepool rescue 15	[-150,158]	No	0
Wavepool rescue 16	[200,123]	No	0
Wavepool rescue 18	[56,48]	Yes	0.05
Wavepool rescue 19	[336,-25]	No	0
Wavepool rescue 20	[129,69]	No	0
Wavepool rescue 21	[-157,192]	No	0
Wavepool rescue 22	[-412,-220]	No	0
Wavepool rescue 23	[230,-199]	No	0
Wavepool rescue 24	[20,170]	No	0
Wavepool rescue 25	[-98,94]	No	0
Wavepool rescue 26	[-212,129]	No	0
Wavepool rescue 27	[-7,-30]	No	0
Wavepool rescue 28	[341,5]	No	0
Wavepool rescue 32	[-571,151]	No	0
Wavepool rescue 34	[-394,128]	No	0
Wavepool rescue 35	[-311,176]	No	0
Wavepool rescue 37	[-297,179]	No	0
Wavepool rescue 38	[-474,105]	No	0
Wavepool rescue 39	[-137,179]	No	0
Wavepool rescue 40	[584,-153]	No	0
Wavepool rescue 41	[115,129]	No	0
Wavepool rescue 42	[-218,184]	No	0

2.1.4 Experiment 5 occlusion study

In Experiment 5, the naturalistic clips were edited to occlude shortly after the onset of drowning (see Table 5). This method was chosen as previous research has shown that occlusion-based tasks show greater differences between experts and novices (Crundall, 2016; Crundall & Eyre-Jackson, 2015; Ventsislavova et al., 2019). This choice of methodology will be defended in Chapter 4.

The occlusion times used for video clips in Experiment 5 were calculated from the first 15 lifeguard and 15 non-lifeguard responses to the reaction-time study used in Experiment 3. The medium response times of these 30 participants to each drowning-present trial was calculated and used for the cut-off for the occlusion. The video footage of each clip prior to occlusion was the same as those used in Experiment 3. The time of occlusion can be seen in Table 5.

A frame was taken from the video footage at the point of occlusion. This was then edited in Adobe Photoshop and given a filter box blur of 20 pixels. A 'no drowning' response box was placed in the right-bottom corner of the image (see Figure 4) and given the response coordinates of $X > 435$ and $Y < -214$. A blurred occlusion screen was chosen over complete occlusion so that participants would still be able to locate where they intended to click. The blurring was sufficient to remove evidence of drowning if one were only exposed to the blurred images.

Figure 4. Two screen shots from the occlusion task: (right) an image from the last frame of the naturalistic drowning clip (left) is the occluded screen with the no drowning response box.

Table 5. The time in ms for the point of occlusion in Experiment 5.

Original clip name	Time of occlusion screen after drowning onset (ms)
Wavepool rescue 1	3320
Wavepool rescue 2	5204
Wavepool rescue 3	9276
Wavepool rescue 4	4027
Wavepool rescue 6	3010
Wavepool rescue 8	3218
Wavepool rescue 9	2352
Wavepool rescue 13	5331
Wavepool rescue 15	7356
Wavepool rescue 16	2226
Wavepool rescue 18	2001
Wavepool rescue 19	1123
Wavepool rescue 20	3709
Wavepool rescue 21	7549
Wavepool rescue 22	6035
Wavepool rescue 23	1784
Wavepool rescue 24	3091
Wavepool rescue 25	2772
Wavepool rescue 26	4426
Wavepool rescue 27	1804
Wavepool rescue 28	1885
Wavepool rescue 32	2545
Wavepool rescue 34	3444
Wavepool rescue 35	8340
Wavepool rescue 37	2475
Wavepool rescue 38	2624
Wavepool rescue 39	2934
Wavepool rescue 40	2544
Wavepool rescue 41	3046
Wavepool rescue 42	2097

2.2 Eye-movements

Previous research has found that lifeguards are better at responding to drowning targets compared to non-lifeguards (Laxton & Crundall, 2018). Experiments 1 and 4 tracked participants' eye-movements to explore if this superior lifeguard drowning detection is driven by better scanning strategies.

Experiments 1 and 4 were created using SMI programme Experiment Centre. The 45 video clips in each experiment were set up to run in a randomised single block, with participants required to make a push button response if they saw a drowning event.

An SMI Red 500 remote eye tracker was used to record eye-movements, sampling at 500 Hz. Fixations and saccades were determined using the software provided with the eye-tracker. A calibration procedure was undertaken prior to testing where participants were asked to fixate on the dots that would move around the display screen. Calibration was validated in the same way. Drift correct fixation points were included between trials. Head movements were not restricted in these experiments. Participants were tracked from an ideal distance of 60cm from the display screen, though they were not held in a chin rest.

2.2.1 Eye-movement data preparation and analysis

In order to analyse the eye-movement data, area of interest (AOI) windows were defined and created for each drowning swimmer trial. These AOIs were only active following onset of the drowning incident and were designed to move with the drowning swimmer if they drifted from the position of drowning onset. AOIs were defined to cover the entire drowning swimmer, whilst keeping background information to a minimum.

All eye-movement data was processed by the SMI software and was prepared for analysis using the programme BeGaze. The AOI's for each drowning trial were created within this programme. The BeGaze software computed all fixation and saccade information relating to those AOIs and these values were reported in a spreadsheet style format. The minimum duration for a fixation to be measured was 80 ms and fixations were calculated from saccadic velocity, with a peak velocity of 40^0/s. The measures explored within these eye-movement data were the number of targets fixated, time to make first fixation to targets, dwell time as a percentage of the AOI and number of fixations made to targets. The values in the spreadsheet were then used to statistically analyse difference in eye-movements.

There are several ways to measure eye-movements (Chen & Choi, 2008; Liversedge & Findley, 2000; Schütz, Braun, & Gegenfurtner, 2011). One of these measures is through saccadic and fixational movements. While saccadic movements allow individuals to rapidly move their eyes to new locations and move objects of interest into foveal vision, this thesis is particularly in interested in fixations to targets. Fixation data allows for the exploration of factors such as where an eye-movement has landed and how long an area is inspected for. Insights into visual attention can be gained from exploring eye-movements (Torralba et al., 2006; Carrasco, 2011). For instance, information on what part of the scene an individual in processing can be gained from fixation locations (Land, 2009; Land & Tatler, 2009). Measures such as fixations durations to areas of the scene may provide an indication of the processing effort, with longer fixations typically given to more complex areas of the scene (Nuthmann, 2017; Rayner, 2009) or shorter fixation durations from domain experts (Gegenfurtner, Lehtinen & Säljö, 2011). In terms of visual selection, there are two types: overt or covert, with overt selection generally performed by eye-movements. Eyes will generally move to areas of interest to retrieve information. However, covert selections are usually performed by visual attention, where attention can still shift to observe the difference properties of that same location (Chen & Choi, 2008; cf Findlay, 2004). Therefore, eye-movements can provide information of what an individual is looking at and help understand the mental process involved, but cannot determine if the fixated area has necessarily been perceived.

The eye-movement measures recorded in this thesis are as follows: the number of targets fixated, the time to first fixation, total dwell time as a percent of the AOI, and number of fixations to targets. These measures were only recorded after drowning onset and all eye-movements were explored independent of whether a correct behavioural response was recorded.

The number of targets fixated was collected as a measure to explore if there were differences in how lifeguards and non-lifeguards detect drowning swimmers. All fixated targets, whether they received a correct response or not, will be considered. This will provide insights to any *looked but failed to see errors,* where targets are being fixated, but are not receiving a correct behavioural response. The time to make the first fixation was collected to explore if expert lifeguards are better able to scan the pool environment and thus make earlier fixations to the target. Dwell as a total percent on the AOI will also be recorded and explored. This is expected to provide insight into how long fixated targets where processed. It is expected that more complex scenes will require longer fixations. Finally, the average number of fixations to targets will be measured, it is expected that those with less experience will make more re-visitations to the target than more experienced participants.

2.3 Apparatus

2.3.1 Experimental computer

In order to collect eye-movement data in Experiments 1 and 4, videos were presented on a Dell computer screen, connected to an SMI RED500 eye tracker sampling at 500Hz. The trials ran in Experiment Centre from a dell laptop.

Experiments 2, 3, 5, 6, and 7 were presented on a Yoga Lenova touch screen laptop, with a screen resolution of 2880x1620.

2.4 Conclusion

In summary, pervious methods of assessing lifeguard visual skills have been limited, with approaches that are impractical for experimental methods (real-life tests), are not realistic (poor computer graphics), or do not reflect the dynamic nature of the task (still images). In this thesis, simulated and naturalistic drownings captured on video were used, which allows for high experimental control, while also allowing for naturally captured behaviours. Participants' responses were recorded in response time tasks, where responses times, accuracy and location accuracy were recorded after drowning onset. Eye-movement measures were also recorded in Experiments 1 and 4, allowing for potential differences between lifeguard and non-lifeguard search strategies to be explored. The method for assessing lifeguard visual skills were also explored, with participants' response accuracy and location accuracy recorded in an occlusion task, where drowning events were occluded shortly after drowning onset.

All other pieces of software or apparatus that were used in the experiments are described in more detail in each of the experimental chapters.

Chapter 3
An investigation into the effect of experience into the visual search for a drowning swimmer in a naturalistic and dynamic task

This experimental chapter aims to extend the findings of Laxton and Crundall (2018). The aim was to provide insight into the superiority of lifeguard visual search through the exploration of lifeguard and non-lifeguard eye movements during a simulated drowning-detection task. Two studies were undertaken. The first attempted to replicate the study of Laxton and Crundall (2018) but with the addition of eye-movement measures. The second study took the basic methodology and tested it across participants with a wider range of lifesaving experience. The results of these two studies help to provide further understanding of lifeguard visual search for a drowning swimmer and further demonstrate the superiority of lifeguard drowning detection in comparison to novice and non-lifeguard participants.

3. Experiment 1

3.1 Introduction

There have been few studies that document lifeguard experiential effects in visual search for drowning swimmers (Laxton & Crundall, 2017; Page et al, 2011; Lanagan-Leitzel & Moore, 2010). Lifeguard superiority in visual search has been noted in these studies, however little is understood in terms of where this superiority lies. For example, Laxton and Crundall (2018) found that lifeguards detected more simulated drownings than non-lifeguards, and they were faster in their responses. However, it is unclear what might be driving these differences between the lifeguards and non-lifeguard participants. Eye-movement measures may offer some insights into differences in visual search between lifeguards and non-lifeguards.

Previous research has explored eye-movements in applied settings and found that expertise and experience in certain domains can positively influence visual processing of items in the scene display. Eye-tracking measures have shown that domain experts have shorter fixation durations and make more fixations to task-relevant areas (Gegenfurtner, Lehtinen & Säljö, 2011; Litchfield et al. 2008). As noted previously, in driving research, Konstantopoulos, Chapman & Crundall (2010) found that driving instructors appeared to have shorter processing times, with shorter fixations distributed across a wider area of the driving display, and broader scanning of the road compared to learner drivers. It appears that, with more experience in driving, attention can be devoted to a wider spatial area, and less processing time is needed.

Based on the reviewed literature in Chapter 1, the first experiment aimed to explore any experiential effects in lifeguards' visual search across individuals with different levels of lifesaving experience, following the method of Laxton and Crundall (2018). This study required participants to make a button response to any instances of active or passive drownings detected in an array of 3, 6, or 9 swimmers. Although lifeguards were shown to have faster and more accurate responses to the drowning swimmers, this study contained potential confounds. The main problem with this 2017 study was that an early response terminated a trial before the drowning event occurred. It is possible that such terminations systematically impacted the performance of non-lifeguards, who were shown to make more premature responses than the lifeguards (17% vs. 7% for non-lifeguards and lifeguards respectively).

To overcome the limitation with premature responses terminating a trial, the current study used a slightly altered method that allowed for multiple responses within a trial. It was predicted that non-lifeguard responses might improve compared to those in the Laxton and Crundall study, resulting in a fairer comparison between our participant groups, though we still predicted lifeguards to remain superior in both search accuracy and response times. To further understand any group differences, eye-movement data was also collected. Based on the literature exploring domain experience, and the task-superiority noted in the 2017 study, it was expected that the lifeguards would be faster to detect targets, with shorter fixation durations and more targets fixated.

Following the Laxton and Crundall study, the set size of the search array was varied (3, 6 or 9 swimmers) as was the type of drowning (active or passive). One possible outcome was that lifeguards would show the greatest superiority over non-lifeguard participants in the hardest conditions for spotting a drowning target (i.e. the largest set size, and when the target is a passive drowning victim. Alternatively, the hardest conditions may have been so difficult as to cause a floor effect nullifying the group differences that occur in the easier conditions.

3.2 Method

3.2.1 Participants

Forty-two participants were recruited to take part in a visual search study (with a mean age of 24.01, SD = 6.07, 22 female). Twenty-one of these participants (mean age 21.14, SD = 4.27, 23-47 age range, 11 females) had completed compulsory qualifications in lifeguarding prior to testing and had a varying amount of experience in poolside lifeguard duties (2.46 years of lifeguarding experience on average). The remaining twenty-one participants (mean age 27.97, SD = 5.87, 16-31 age range, 11 females) had no lifeguarding experience. Lifeguards were recruited from a local leisure centre in the Leicestershire area, and through Nottingham Trent University. Non-lifeguard participants were an opportunistic sample from Nottingham Trent University, made up from a majority of postgraduate students and research assistants.

3.2.2 Design

A 2 x 2 x 3 mixed design was employed, comparing experience groups (lifeguards to non-lifeguard participants), drowning type (15 active drowning trials and 15 passive drowning trials) and set size of the search array (with 3, 6, or 9 swimmers). In addition to the active and passive drowning targets, 15 non-drowning trials were also included. Of the 15 trials for each of the drowning and control stimuli sets, five trials contained 3 swimmers, five trials contained 6 swimmers and five trials contained 9 swimmers. During presentation to participants, all trials were randomised within a single block. All participants viewed all trials. Accuracy and response times to detect the drowning target were recorded. In order to overcome the problem with premature responses being recorded as incorrect in a previous experiment (Laxton & Crundall, 2018), participants in this experiment were allowed to make multiple responses. However, if participants made a premature response, which was not followed by a correct response, this was coded as an incorrect false alarm. Alternatively, if no response was made this was also coded as incorrect. Participants were aware that they could press more than once, though they were discouraged from responding more than once, and were told that – should a drowning event occur – there will be only one per clip. Participant's eye movements in each trial were also recorded.

Drownings lasted on average 11 seconds in length from the first indication of drowning to the completion of the clip, which lasted an average of 30 seconds. All measures, both in the behavioural data and the eye-movement data, were taken from the onset of the drowning, with onset to clip-end forming a drowning window for responses.

3.2.3 Apparatus and Stimuli

The stimuli were developed for an MSc project, subsequently reported in Laxton and Crundall (2018). The development of these stimuli is detailed here for the sake of completeness. Initial video footage was recorded on a Samsung Galaxy EK-GC110 23mm handheld digital camera, up on a standard tripod. The camera was pointed down the length of the pool, capturing the shallow end of a 25 by 15 metre pool, but also environmental features, such as the poolside equipment, windows with views into a gym corridor and a pool-side clock on the distant wall (see Figure 1). The swimmers in the video footage were volunteers recruited from local lifesaving clubs and had prior training in drowning simulation. All volunteers gave informed written consent before taking part in any filming.

Swimmers were placed in a 10m by 15m section of the pool, all within visibility of the camera, and asked to swim across the 15m width of the pool. A variety of swimming strokes were used by the swimmers. In the active drowning video clips, a swimmer was primed, on cue, to become distressed in the water, showing signs of panicking and visibly struggling or displaying an instinctive drowning behaviour (Vittone & Pia, 2006). In passive drowning clips, on cue again, a swimmer would become motionless and face down in the water, in accordance with research presented in the literature (Fenner et al. 1999). The cameraperson was able to use verbal cues and a whistle during filming to direct the action, as the result stimuli are presented without an audio track. During filming every volunteer swimmer was able to perform both drowning types across different set sizes to ensure variety of targets.

Forty-five clips were selected from the footage, evenly distributed across the active, passive and non-drowning levels. Within each level of the drowning-type factor, an even number of 3, 6 and 9 swimmer trials were selected (5 of each per drowning type). The clips lasted an average of 30 seconds. The drowning incidents lasted an average of 11 seconds with clips ending immediately following the drowning (see Table 1). Both types of drownings happened quasi-randomly within the second half of an average length video clip.

The stimuli were identical to those used in Laxton & Crundall (2018), with the exception that the videos were presented on a Dell computer screen, connected to an SMI RED500 eye tracker sampling at 500Hz. The trials ran in Experiment Centre as a randomised block. A fixation cross was shown before each new clip. If participants stared at this cross for half a second, the next trial would begin.

3.2.4 Procedure

In order to recruit lifeguards, the experimenter arranged testing sessions at various pools and leisure centres around Nottingham and Leicester, with a quiet office or side-room acting as the laboratory. Non-lifeguard participants were tested under similar conditions. Participants were given written instructions and asked to fill in a consent form and demographic questionnaire. Prior to the study, participants were made aware that they would be searching for any potentially drowning victims from a lifeguard's perspective, and that the study would contain active, passive and non-drowning trials. Definitions of the drowning types were also provided. Participants were told they could make multiple responses, but to only respond once to any drowning incidents they observed.

This was to reduce the number of premature responses participants made to clips. Participants were made aware that each drowning trial only contained one drowning incident; however, they could make multiple responses if they thought they had made a false alarm response. If a drowning was identified, participants were told to press the zero key on the number pad of a standard keyboard. Once all instructions had been given participants were given the opportunity to complete a practice trial, which was followed by a final opportunity to ask any remaining questions before the experimental block began. The experimental block was preceded by a calibration procedure to ensure the eye tracker could identify the location of the participants' eyes. This required them to follow a moving cursor with their eyes while sat at 60 cm distance from the screen. When the participant had been correctly calibrated to the eye tracker the test began. Upon finishing the test, the participants were fully debriefed and thanked for their time and participation. This research was conducted with approval obtained from Nottingham Trent University ethics committee and run in accordance of British Psychological Society guidelines.

3.3 Results

3.3.1 Behavioural data

A 3 x 2 x 2 mixed ANOVA compared set size (3, 6 and 9) across group (lifeguards and non-lifeguards) and drowning type (active or passive). As participants' lifeguarding experience was the focus of this research, only significant interactions that included factor are explored. If set size produced a significant main effect or was involved in a significant interaction with experience, then planned comparisons were employed, comparing set sizes 3 and 6, and set sizes

6 and 9 (including the experience factor in order to identify the locus of the interaction). Where significant interactions required further exploration, t-tests were used, in which case they were adjusted for multiple comparisons using the Bonferroni correction.

A multiple regression will also be performed, with the accuracy of responses and the response times as outcome variables. Demographic information (experience, age, gender) will be included as the predictor variables. This will allow for the relationship between these variables to be explored. In Experiment 1, the association between swimming experience and own swimming confidence will be explored alongside the demographic information, to see if more swimming experience is associated with better performance in the drowning detection task (see section 3.3.2). In Experiment 2, education will be included as a predictor variable in addition to the demographic information, to explore if the higher education level of participants is associated with better performance in the drowning detection task (see section 3.7.2).

3.3.1.1 Catch trial responses

The response rates to the non-drowning trials were first assessed. On average, non-lifeguard participants incorrectly responded to 5.1% of catch trials, while lifeguards were less successful with 15.6% ($t(40) = 2.59$, $p < 0.05$).

3.3.1.2 Signal detection analysis

The measures of *d'* (a measure of sensitivity to the signal; zHits – zFalse Alarms) and *c* (the criterion to say yes regardless of the information; (zHits + zFalse Alarms)/2) were calculated for each experience group and then compared.

Accuracy for detecting a drowning target (i.e. making a response within the drowning window) was subjected to signal detection analysis. Neither *d'* ($t(40)$ = 1.01, p = 0.3) or *c* ($t(40)$ = -1.27, p = 0.2) were found to differ significantly between the two groups. This suggests that there was no difference between the participants likelihood to detect the target and their likelihood to say 'yes' to the signal. All subsequent analysis focuses on trials on which there was a target.

3.3.1.3 Behavioural measures

The percentage of trials with a drowning target that were correctly responded to were then analysed. Trials with a drowning target were considered incorrectly responded to if no response was made following the onset of drowning activity. Correct responses were converted into percentages of the total drowning trials in each condition and subjected to a group x drowning type x set size (2 x 2 x 3) mixed ANOVA.

Unlike Laxton and Crundall (2018), a main effect was not found for experience group on accuracy rates ($F(1,40) = 1.3$, MSe = 387.5, $p = 0.26$, $\eta_p^2 = 0.03$). Though the lifeguards identified 89.5% compared to the non-lifeguards 84.6%, this difference was not significant. The difference between accuracy for active trials and passive trials (84.9% vs. 89.2%), and the main effect of set size (89.5% vs. 87.6% vs. 84.0%, across set sizes 3, 6 and 9 respectively), also failed to reach significance, despite ostensible trends.

Two interactions were significant however. First, an interaction between set size and experience group was explored ($F(2,80) = 4.6$, MSe = 231.8, $p < 0.05$, η_p^2 = 0.10).

All effects involving set-size were investigated with planned contrasts comparing set size 3 with set size 6 and set-size 6 to set-size 9. For this particular analysis, the repeated contrasts identified the interaction to lie between set size 6 and set size 9 ($F(1,40) = 8.1$, $MSe = 461.9$, $p < 0.05$, $\eta_p^2 = 0.17$). As can be seen from Figure 5 lifeguards appear to outperform non-lifeguards on set sizes 3 and 6, though these groups produced comparable levels of performance at set size 9.

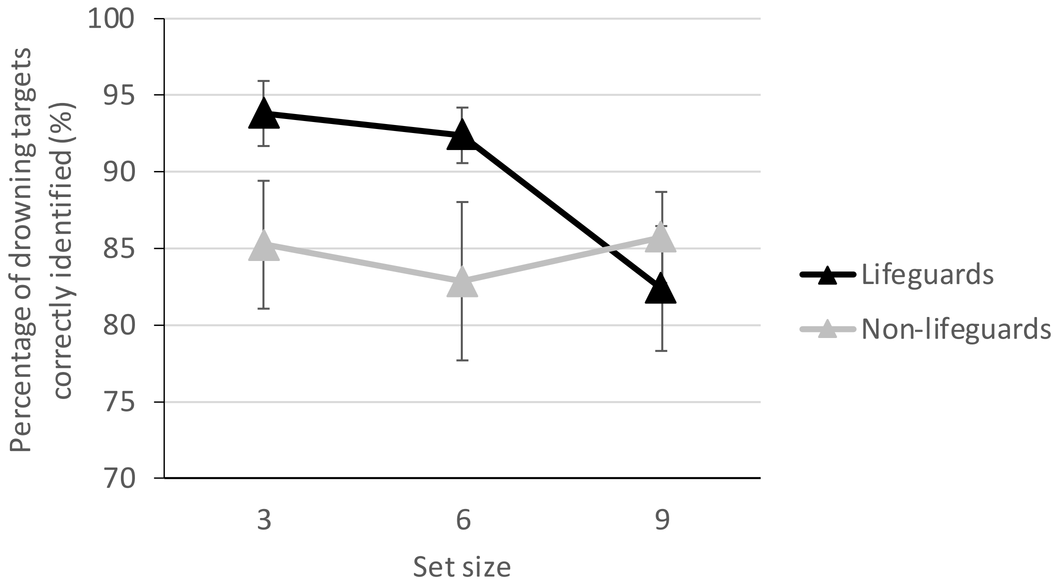


Figure 5. The mean percentages of trials containing drowning targets that were accurately responded to (with standard error bars)

A second interaction was noted between drowning type and set size ($F(2,80) = 5.4$, $MSe = 240.7$, $p < 0.05$, $\eta_p^2 = 0.12$). The repeated contrasts identified the interaction to be driven by responses to active and passive trials in set size 6, which were significantly different to responses in set sizes 3 and 9 (set size 3 vs. 6: ($F(1,40) = 12.5$, $MSe = 298.1$, $p < 0.05$, $\eta_p^2 = 0.24$) and set size 6 vs. 9: ($F(1,40) = 7.8$, $MSe = 512.4$, $p < 0.05$, $\eta_p^2 = 0.16$). Figure 6 appears to show that passive trials are correctly responded to more frequently than active trials but only when 3 or

9 swimmers were present. Post hoc Bonferroni corrected t-tests revealed that active and passive accuracy only differ at set size 3 ($t(41) = 2.6$, $p < 0.017$).

To further investigate the interaction, two one-way ANOVAs were carried out comparing set size levels for each drowning type separately. For active drownings the main effect of set size remained significant ($F(2,82) = 3.4$, $MSe = 332.8$, $p < 0.05$, $\eta_p^2 = 0.08$). Planned repeated contrasts suggested that the main effect is driven by the difference between set size 6 and 9 ($F(1,41) = 2.9$, $MSe = 843.7$, $p < 0.05$, $\eta_p^2 = 0.12$). Passive drownings also produced a main effect of set size ($F(2,82) = 4.6$, $MSe = 169.4$, $p < 0.05$, $\eta_p^2 = 0.10$), with planned repeated contrasts demonstrating the interaction to lie between set size 3 and 6 ($F(1,41) = 6.8$, $MSe = 451.6$, $p < 0.05$, $\eta_p^2 = 0.14$).

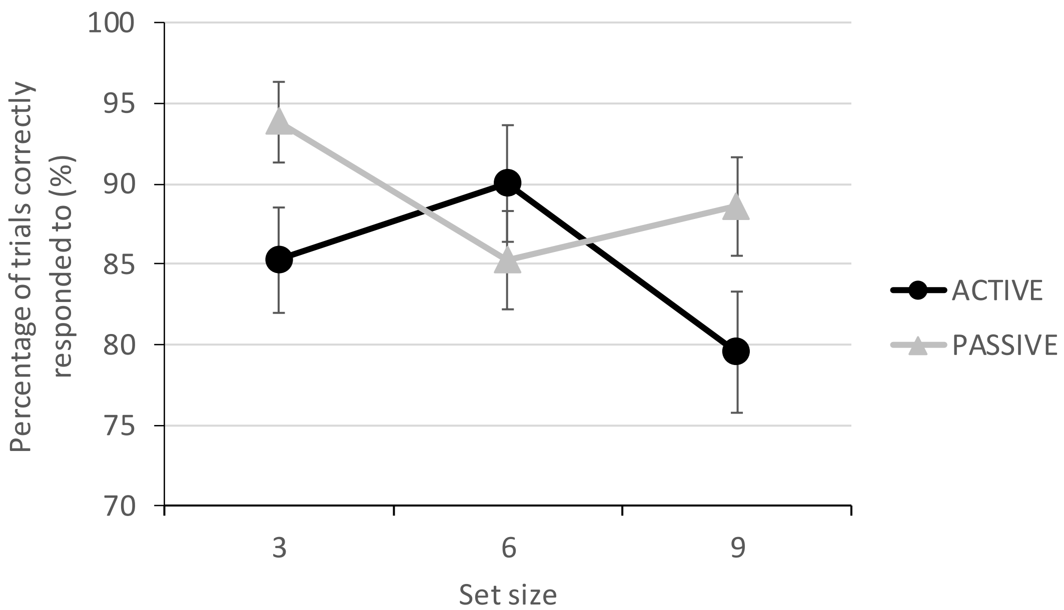


Figure 6. The mean percentages of drowning trials that were correctly responded to (with standard error bars)

Response times were subjected to a similar 2 x 2 x 3 ANOVA (group x drowning type x set size). One participant, who did not response to any drownings in the set size 6 condition, was removed from the analysis. Main effects were found for all three factors. First a experience group effect was noted ($F(1,39) = 4.2$, $MSe = 2603666$, $p < 0.05$, $\eta_p^2 = 0.10$), with lifeguards identifying drowning targets nearly a second faster than non-lifeguard participants (4215 ms vs. 4935 ms). The main effect of drowning type ($F(1,39) = 20.80$, $MSe = 3198316$, $p < 0.001$, $\eta_p^2 = 0.35$) revealed passive drownings were identified over a second faster than active drownings (4051 ms vs. 5092 ms). The main effect of set size (F2,70) = 8.7, $MSe = 1449725$, $p < 0.001$, $\eta_p^2 = 0.18$) reflects an ostensible increase in RTs with an increase in distractors (4125 ms, 4723 ms and 4865 ms for set sizes 3, 6, and 9, respectively). Planned repeated contrasts demonstrate that set size 3 evoked faster RTs than set size 6 ($F(1,39) = 12.2$, $MSe = 2274287$, $p < 0.05$, $\eta_p^2 = 0.25$).

The only significant interaction was found between drowning type and set size ($F(2,78) = 6.0$, $MSe = 1555115$, $p < 0.05$, $\eta_p^2 = 0.14$). Planned repeated contrasts show that this interaction is driven by a difference between set size 3 and 6 ($F(1,39) = 12.2$, $MSe = 2220835$, $p < 0.05$, $\eta_p^2 = 0.24$), and between set sizes 6 and 9 ($F(1,39) = 8.3$, $MSe = 3504505$, $p < 0.05$, $\eta_p^2 = 0.18$). Figure 7 shows that RTs to active drownings are slowed most when switching from 3 swimmers to 6 swimmers. Conversely, passive drownings are still responded to as quickly at set size 6 as they are at set size 3. It is only at set size 9 that responses to passive drowning are significantly slowed. It can also be seen that the difference between reaction time for the drowning types is largest in the set size 6. Post hoc

Bonferroni adjusted t-tests support this interpretation with active drownings at set size 3 being different from active drownings at set size 6 ($t(40) = -4.7$, $p < 0.001$), and passive drownings at set size 6 being different from set size 9 ($t(40) = -3.2$, $p < 0.007$). Differences between active and passive drownings at set size 6 were also supported ($t(40)= 6.5$, $p < 0.001$).

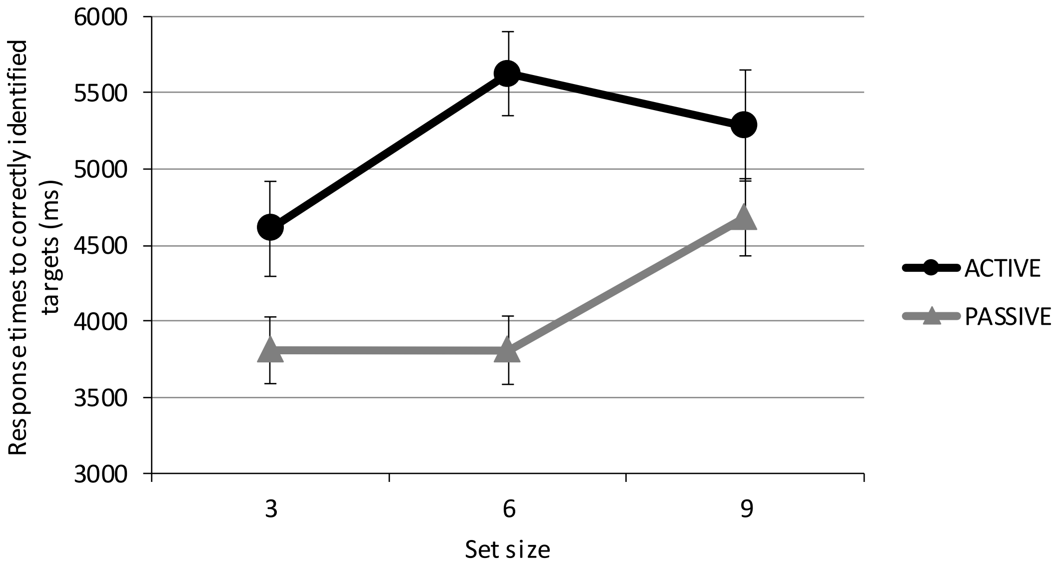


Figure 7. The mean response time to drowning trials that were correctly responded to (with standard error bars).

3.3.2 Regression Analysis

In order to explore whether response accuracy or RT were related to individual differences measured we completed two multiple regressions with demographic information: age, gender, lifeguarding experience in years, number of hours spent swimming in a year, and confidence in own swimming ability as the predictor values. The first regression examined whether these predicted the response accuracy. The means and SDs for each variable can be seen in Table 6. The overall model was not significant ($F(5,36) = 0.47$, $p = 0.798$).

Table 6. The means and SDs of the dependant variable and the predictor values, and the correlation matrix for drowning detection accuracy.

Variable	Mean	Sd	1.	2.	3.	4.	5	6.
1. Accuracy	87.06%	13.97	1					
2. Experience	1.14	2.53	.105	1				
3. Age	24.56	6.14	-.185	-.076	1			
4. Gender	1.52	0.51	-.076	-.042	.082	1		
5. Hours Swimming	190	799.01	.102	.863**	.119	-.126	1	
6. Confidence	7.29	2.71	.168	.358*	-.319	-.200	.211	1

Notes: *P < 0.05, **P < 0.001

None of the individual predictors in the model were significant on their own (see Table 7).

Table 7. Summary of Simple Regression Analyses for Variables Predicting drowning detection accuracy and reponse times to drowning detection.

Variable	*Drowning Detection Accuracy*			*Response times*		
	B	*SE B*	*β*	**B**	*SE B*	*β*
Constant	94.13	15.65		4758.56	1340.55	
Experience	-0.72	2.01	-0.13	-280.51	172.40	-0.01
Age	-0.41	0.41	-0.19	-2.72	35.36	-0.58
Gender	-0.51	4.71	-0.02	170.70	403.25	-0.07
Hours Swimming	0.00	0.01	0.21	0.73	0.54	0.48
Confidence	0.56	0.97	0.11	-30.71	82.66	-0.07

Notes: *P < 0.05, **P < 0.001

The second regression examined whether these predictors predicted response time. The overall mean response time was 4546 ms (SD 1225 ms). Correlations between variables can be seen in Table 8. The overall relationship was not significant ($F(5,36) = 0.84$, $p = 0.532$).

Table 8. Correlation matrix for the predictor and outcome variables for the response times.

Variable	1.	2.	3.	4.	5.	6.
1. Accuracy	1					
2. Experience	-.195	1				
3. Age	.115	-.076	1			
4. Gender	.047	-.042	.082	1		
5. Hours Swimming	-.049	.863**	.119	-.126	1	
6. Confidence	-.185	.358*	-.319*	-.200	.211	1

Notes: *P < 0.05, **P < 0.001

None of the individual predictors in the model were significant on their own (see Table 6).

3.3.3 Eye-movement measures

The results for the number of drowning swimmers that were fixated after drowning onset were analysed first within the eye-movement data. A fixation on a drowning target was only considered relevant if it occurred within the drowning window. The number of targets that received a fixation were converted into percentages of total targets and subjected to a group x drowning type x set size (2 x 2 x 3) mixed ANOVA.

The main effect of experience group was not significant (F(1,40) = 0.04, MSe = 205.3, p = 0.84, η_p^2 = 0.00), with both lifeguards and non-lifeguards fixating a similar number of targets (94.9% for the lifeguards and 94.3% for the non-lifeguards). However, main effects were found for both drowning type and set size. The main effect of drowning type (F(1,40) = 4.6, MSe = 34.6, p < 0.05, η_p^2 =

0.10) identified that passive drownings were more likely to be fixated than active drownings (95.4% vs. 93.8%). The main effect of set size was also significant ($F(2,80) = 4.6$, $MSe = 77.9$, $p < 0.05$, $\eta_p^2 = 0.10$). Planned repeated comparisons between set size 3 vs. 6 and set size 6 vs. 9 showed no significant differences in fixation percentages. As such the additional t-test (Bonferroni adjusted) between set size 3 and 9 was run which showed that fewer targets fixated at set size 3 than set size 9 (92.4% vs. 97.4%) ($t(41) = -2.6$, $p < 0.017$).

A three-way interaction between experience group x drowning type x set size was found to be significant ($F(2,80) = 3.3$, $MSe = 91.9$, $p < 0.05$, $\eta_p^2 = 0.08$). Figure 8 shows that this appears to be driven by the number of targets fixated by lifeguard participants, which seem to be differentially affected by the increase in set size across drowning target type. Lifeguards are close to ceiling in terms of the number of targets fixated in set size 6 for passive drowning trials, though this number decreases slightly in set size 9. However, with active drownings there is an increase in the number of fixated targets at set size 9 compared to set size 6. Non-lifeguard participants' likelihood of fixating the targets is the same, regardless of drowning type, and follows the pattern of results produced by lifeguards when fixating active targets.

To unpack this interaction two experience group x set size mixed ANOVAs were carried out for each drowning type. In the active drowning conditions the main effect of set size remained ($F(2,80) = 5.1$, $MSe = 72.5$, $p < 0.01$, $\eta_p^2 = 0.11$), with planned repeated contrasts demonstrating the effect to lie between set size 6 and 9 ($F(1,40) = 7.4$, $MSe = 184.8$, $p < 0.05$, $\eta_p^2 = 0.16$). This supports the interpretation that more targets are fixated in the set size 9 than in the set size 6 for active drownings (97.1% for set size 9 and 91.4% for set size 6). There was no main effect of, or interaction with, experience in relation to fixations on active targets.

The second group x set size ANOVA for the passive target condition (experience x set size) did not reveal a main effect of set size ($F(2,80) = 2.8$, $MSe = 138.9$, $p = 0.07$, $\eta_p^2 = 0.07$). While this did not reach conventional significance, planned repeated contrasts suggest a difference between set size 3 and set size 6 ($F(1,40) = 4.0$, $MSe = 236.2$, $p = 0.05$, $\eta_p^2 = 0.09$) with passive targets more likely to be fixated at set size 6 than set size 3. Planned contrasts also suggested that the non-significant omnibus interaction between experience and set size, belied a difference between set sizes 6 and 9 across the groups ($F(2,80) = 4.0$, $MSe = 236.2$, $p = 0.05$, $\eta_p^2 = 0.09$). As can be seen in Figure 8 lifeguards appear to fixate more passive targets than non-lifeguards at set size 6, though this effect is reversed at set size 9.

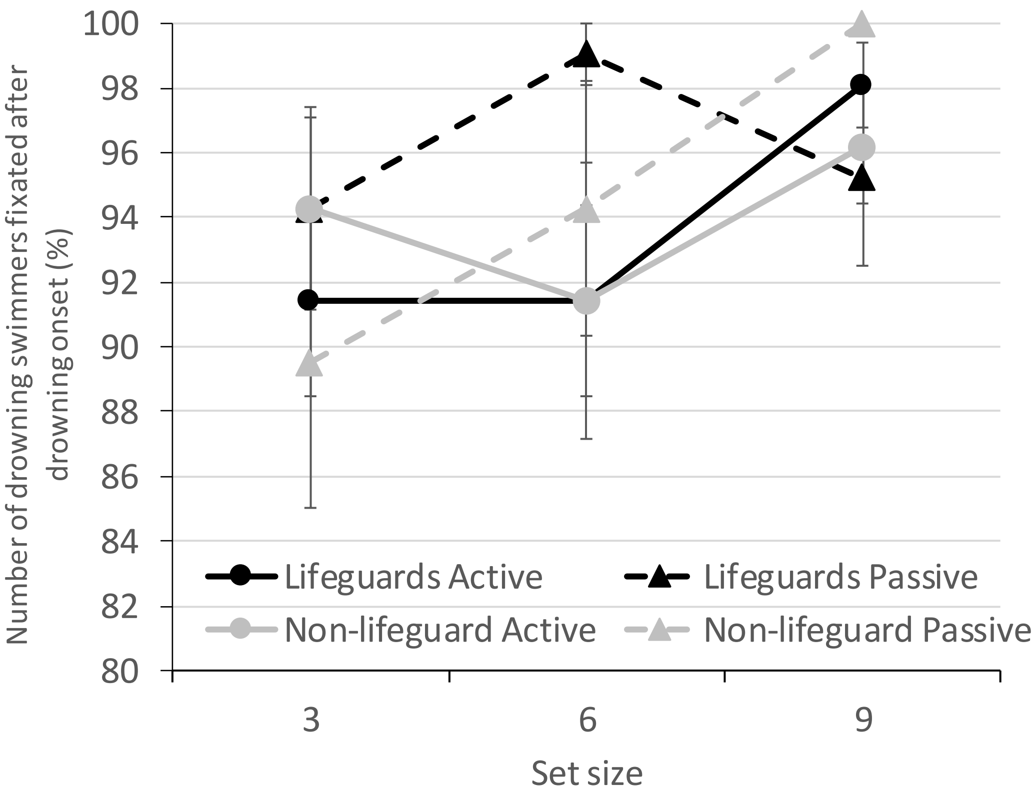


Figure 8. The mean percentages of the number of targets that were fixated after drowning onset (with standard error bars).

The time (ms) to make the first fixation on the target (calculated from drowning onset) was subjected to a similar 2 x 2 x 3 ANOVA. A main effect for drowning type was found (F(1,40) = 14.1, MSe = 1117547, $p < 0.05$, η_p^2 = 0.26), with passive drowning trials receiving an initial fixation an average of 500 ms before active drowning trial (1615 ms vs. 2136 ms). The other two main effects failed to reach significance, although lifeguards were faster to fixate the drowning target than the non-lifeguards (1667 ms vs 2023 ms respectively).

An interaction between drowning type and set size proved to be significant (F(2,80) = 4.0, MSe = 1051012, $p < 0.05$, η_p^2 = 0.09). Planned repeated contrasts show that the difference between set size 3 and 6 just fell above the conventional level of significance (F(1,40) = 3.8, MSe = 2210399, p = 0.057, η_p^2 =

0.09). The interaction is primarily driven by the difference between set size 6 and 9 (F(1,40) = 6.9, MSe = 1946190, $p < 0.05$, $\eta_p^2 = 0.17$). Figure 9 appears to show that the difference lies in the time to first fixate passive drownings in these set sizes. A difference also appears to lie between the drowning types in set size 6. Post hoc Bonferroni adjusted t-tests reveal that the difference between active and passive drownings at set size 6 was significant ($t(1,40) = 4.1$, $p < 0.001$).

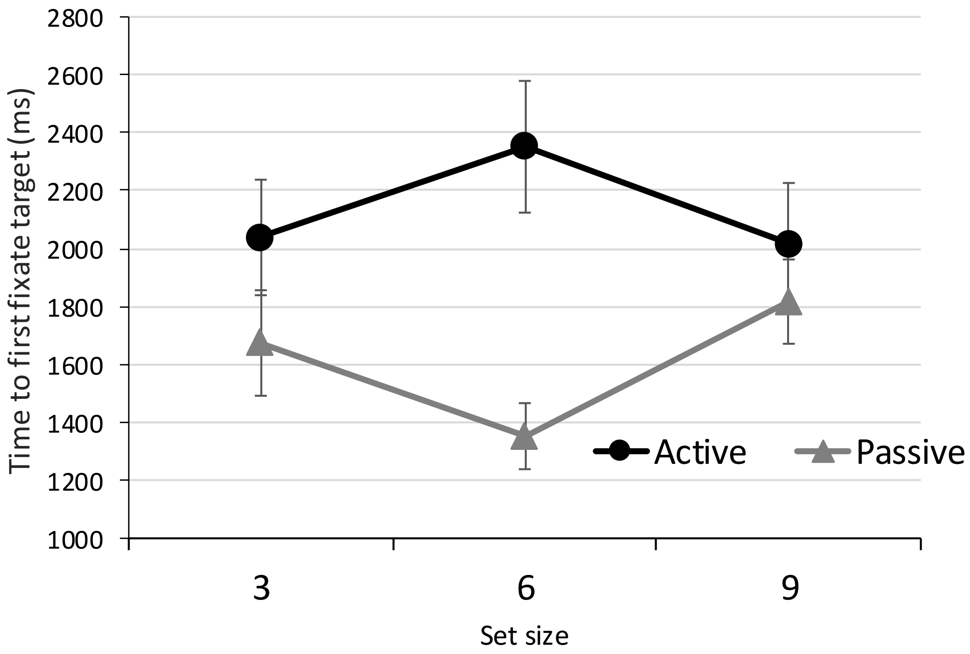


Figure 9. Time to first fixate targets in ms (with standard error bars)

Dwell times, as a percentage of the drowning window, were also subjected to a 2 x 2 x 3 ANOVA. There was no effect of experience, with non-lifeugards having longer dwell on targets than lifeguards (39.5% vs. 34.3%). There was a main effect of both drowning type (F(1,40) = 7.3, MSe = 72.2, $p < 0.05$, $\eta_p^2 = 0.15$) and set size (F(2,80) = 6.7, MSe = 79.7, $p < 0.05$, $\eta_p^2 = 0.14$), but these are best explained by the interaction between these two factors size (F(2,80) = 5.2, MSe =

57.5, p < 0.05, η_p^2 = 0.12). Figure 10 shows that at set size 9 for passive drowning trials, dwell times in the AOI window are much shorter than in any other condition. Post-hoc t-tests support this pattern of results (set size 3: t(41) = 0.85, p = 0.4; set size 6: t(41) = 0.1, p = 0.9; set size 9: t(41) = 4.4, p < 0.001).

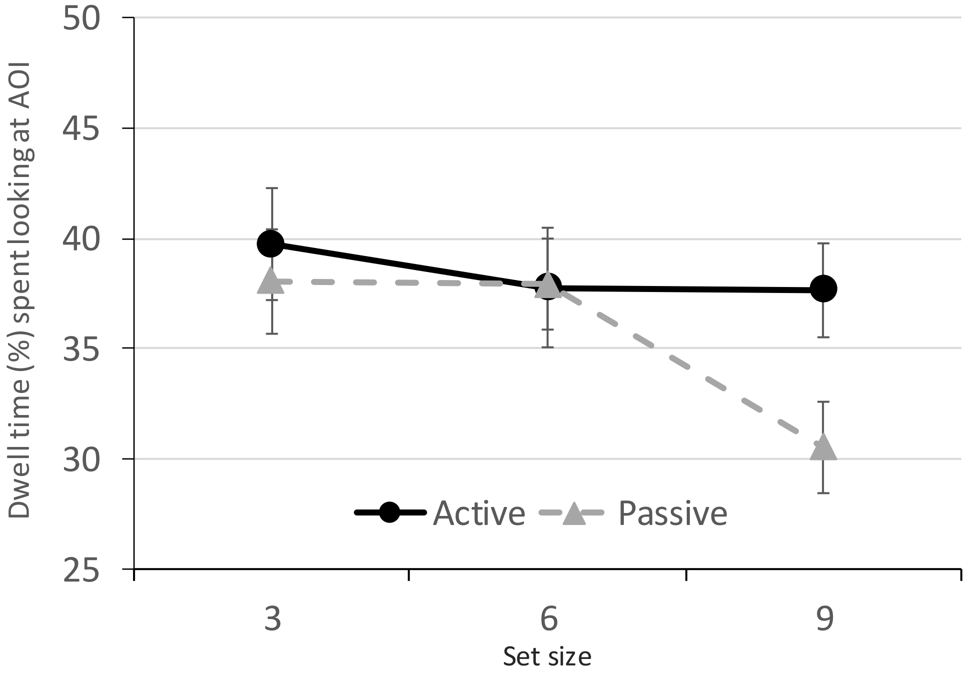


Figure 10. Average dwell time as a percentage of the total time that they could have looked at the target (with standard error bars)

The mean number of fixations on the targets was subjected to a 2 x 2 x 3 mixed ANOVA (group x drowning types x set size). No difference was found between experience groups (non-lifeguards 9.8 and lifeguards 10.0), however, main effects were found for drowning type and set size. First, drowning type (F(1,40) = 17.6, MSe = 6.7, p < 0.001, η_p^2 = 0.31) revealed that active drowning targets received more fixations than passive (10.5 vs. 9.2). The main effect of set size (F(2,80) = 13.6, MSe = 5.8, p < 0.001, η_p^2 = 0.25) noted a linear increase in the number of fixations as set size increased (8.9 vs. 10.0 vs. 10.8). Planned repeated contrasts revealed that set size 3 was different from set size 6 ($F(1,40) = 9.2$, MSe = 11.2, $p < 0.005$, $\eta_p^2 = 0.19$), and set size 6 was different from set size 9 ($F(1,40) = 5.6$, MSe = 10.2, $p < 0.05$, $\eta_p^2 = 0.12$).

One interaction was subsumed by a 3-way interaction between group x drowning type x set size ($F(2,80) = 3.9$, MSe = 4.6, $p < 0.05$, $\eta_p^2 = 0.09$). From Figure 11 this appears to be driven by the difference in the number of fixations on active and passive targets made by non-lifeguard participants at set sizes 3 and 9. Lifeguard participants also appear to differ in the number of fixations given to active and passive targets at set size 9.

To unpack this interaction two drowning type x set size ANOVAs were conducted for each experience group. For the non-lifeguards the main effect of drowning type remained, with active targets receiving more fixations than passive targets ($F(1,20) = 14.2$, MSe = 4.2, $p < 0.05$, $\eta_p^2 = 0.42$), as did that of set size ($F(2,40) = 15.0$, MSe = 3.2, $p < 0.001$, $\eta_p^2 = 0.43$). Planned repeated contrasts show that the set-size effect was driven by the difference between set size 6 and 9 ($F(1,20) = 10.1$, MSe = 8.8, $p < 0.05$, $\eta_p^2 = 0.34$), with drownings in set size 9 receiving more fixations than drowning swimmers in set size 6.

The interaction between drowning type and set size also remained significant for non-lifeguards ($F(2,40) = 3.2$, MSe = 4.9, $P < 0.05$, $\eta_p^2 = 0.47$). Planned repeated contrasts show that the interaction is driven by differences between set size 3 and 6 ($F(1,20) = 22.73$, MSe = 8.0, $p < 0.001$, $\eta_p^2 = 0.53$) and differences between set size 6 and 9 ($F(1,20) = 28.3$, MSe = 8.9, $p < 0.05$, $\eta_p^2 = 0.59$). Post hoc

Bonferroni corrected t-tests reveal that active drownings at set size 6 were fixated less than active drownings at set size 9 ($t(20) = -6.2$, $p < 0.001$). At set size 9, active drownings were found to be fixated more often than passive drownings ($t(20) = 4.4$, $p < 0.001$). A difference was also noted between passive drownings at set size 3 and set size 6 ($t(20) = -3.8$, $p < 0.007$), with targets at set size three being fixated less than at set size 6. Finally, a difference was noted between active and passive drownings at set size 3 ($t(20) = 4.4$, $p < 0.001$), with active drownings being fixated more often than passive.

The second two way ANOVA (drowning type x set size) for the lifeguard participants also showed the main effects of drowning type ($F(1,20) = 6.2$, $MSe = 9.2$, $p < 0.05$, $\eta_p^2 = 0.24$), with active drownings fixated more often than passive, and set size ($F(2,40) = 4.1$, $MSe = 8.4$, $p < 0.05$, $\eta_p^2 = 0.17$), with drownings at set size 3 being fixated less than at set size 6. The interaction between drowning type and set size also remained significant ($F(2,40) = 3.2$, $MSe = 4.9$, $p < 0.05$, $\eta_p^2 = 0.14$), with planned repeated contrasts noting the interaction lies between set sizes 6 and 9 ($F(1,20) = 58.9$, $MSe = 7.4$, $p < 0.05$, $\eta_p^2 = 0.21$). Post hoc Bonferroni adjusted t-tests support this with the only significant difference being found between active and passive drowning targets at set size 9 ($t(20) = 3.5$, $p < 0.007$), with active targets being fixated more often than passive.

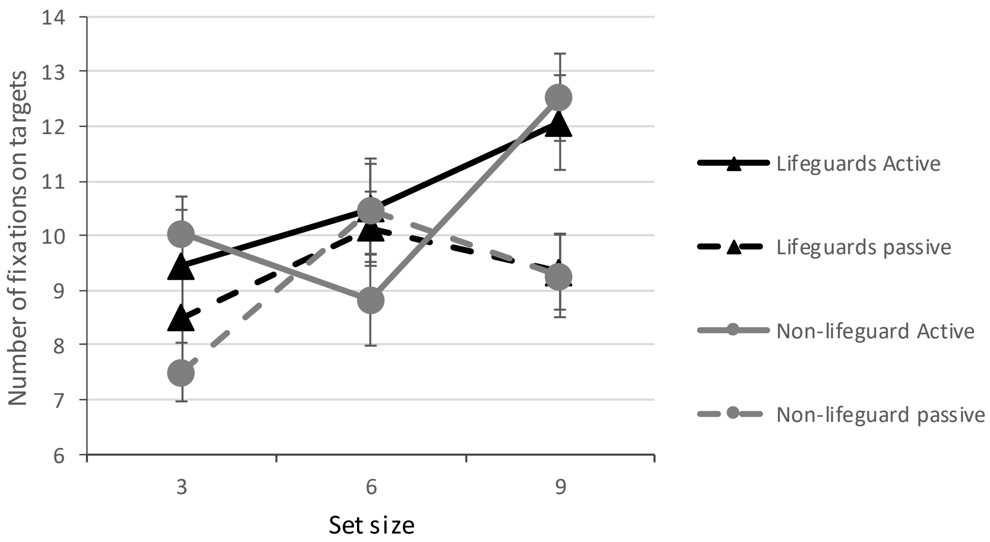


Figure 11. Average number of fixations made to the active and passive drowning targets (with standard error bars)

3.3.3.2 Processing times

Further analysis was conducted, looking at the time between first fixations and first correct response. One participant was removed from the analysis due to all fixation data being missing for one condition. The time between the first fixation to the target and a behavioural response was calculated to assess processing time; responses where a target was not fixated were not included in the analysis. This was then subjected to a group x drowning type x set size (2 x 2 x 3) mixed ANOVA.

The main effect of drowning type ($F(1,39) = 28.9$, $MSe = 3881618$, $p < 0.001$, $\eta_p^2 = 0.43$) revealed that passive drownings had less time between first fixation and the response time than the active drownings (2502 ms vs. 3854 ms respectively). The main effect of set size ($F(2,78) = 5.0$, $MSe = 3071594$, $p < 0.05$, $\eta_p^2 = 0.11$), when subjected to planned repeated contrasts, revealed that set size 3 differed to set size 6 ($F(1,39) = 8.6$, $MSe = 5457085$, $p < 0.05$, $\eta_p^2 = 0.18$), but set size 6 did not differ from set size 9 ($F(1,39) = 0.001$, $MSe = 707340$, $p = 0.742$) (set size 3: 2677 ms, set size 6: 3433 ms, set size 9: 3424 ms). The main effect of experience failed to reach significance, although lifeguards had shorter processing times compared to non-lifeguards (2981 ms vs 3376 ms, respectively).

One interaction between set size and drowning type was noted ($F(2,78) = 3.3$, $MSe = 2919664$, $p < 0.05$, $\eta_p^2 = 0.08$). Planned repeated contrasts show that the interaction lies between set size 3 and 6 ($F(1,39) = 4.2$, $MSe = 5663559$, $p < 0.05$, $\eta_p^2 = 0.10$). From Figure 12 this appears to be driven by the slowed time between set size 3 and 6 in active drownings. Post hoc Bonferroni adjusted t-tests support this interpretation, with the time between first fixation and response times being smaller in set size 3 for active drownings than at set size 6 ($t(40) = -3.4$, $MSe = 387.4$, $p < 0.007$) (2963 ms vs 4255 ms set size 3 and 6 respectively). Differences between active and passive drownings at set size 6 were also found ($t(40) = 4.7$, $MSe = 350.9$, $p < 0.001$), with passive drownings having a faster time between first fixation and response than active drownings (2611 ms vs 4256 ms respectively). A difference between active and passive drownings in set size 9 was also significant ($t(40) = 4.6$, $MSe = 401.8$, $p < 0.001$). Again, passive drownings had the faster time between first fixation and response time than active (2505 ms vs 4343 ms). It should be noted that the active drownings have the longer time to first fixate, therefore these shorter processing times of passive drowning are not curtailed by the end of the clip.

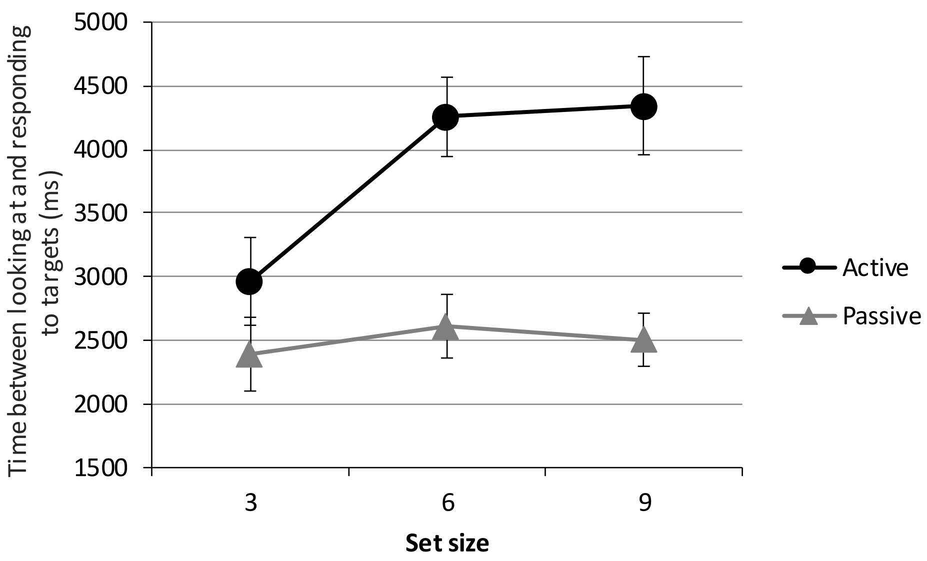


Figure 12. Time between first fixation and behavioural response in trials that received correct responses in ms (with standard error bars)

3.4 Discussion

The results of Experiment 1 have confirmed the predicted superiority in the visual search of lifeguards in drowning simulations, but this was primarily demonstrated in their response times to drowning targets. Lifeguards were found to detect drowning swimmers nearly a second faster, on average, than non-lifeguards. In regard to the accuracy of responses to drowning swimmers, lifeguards were found to outperform the non-lifeguard participants at the small and intermediate set sizes.

Lifeguard superiority on both of these measures fits with previous studies that have demonstrated expert superiority in detecting targets in static image searches (Biggs & Mitroff, 2014: Nodine et al. 2002; Curran et al. 2009), and for detecting events in complex dynamic environments (Howard et al. 2010; Howard et al. 2013; Troscianko et al. 2004). This result confirms the lifeguard superiority noted in Laxton and Crundall (2018), even after the confound of premature trial termination had been removed.

The clear response time advantage for lifeguards in these dynamic real-world scenes may be a result of their training and experience. Through exposure and training, these experts have repeatedly witnessed a variety of natural swimming behaviours and will no doubt have encountered potential drowning events either from real incidents or from simulated scenarios during lifeguard training. Such perceptual learning is likely to have increased their ability to detect drowning characteristics.

The accuracy of results in Experiment 1 differ to those of Laxton and Crundall (2018). In that study, lifeguards were found to detect more simulated drownings and respond to them faster across all set sizes, whereas the current data showed no difference at set size 9 in terms of accuracy. Compared to Laxton and Crundall (2018), a number of interesting factors appear (see Figure 13). First, the current non-lifeguard participants are ostensibly performing better in the passive drowning condition. While the lifeguards across the two studies identified 87.9% and 90.4% of drowning targets in the passive condition, the non-lifeguard groups from the two studies correctly reported 72.0% and 88.4%, respectively. Second, it appears that the lifeguards in the current study are adversely affected by active drowning targets in the highest set size. While the lifeguards in Laxton and Crundall (2018) appear to detect a similar number of active drowning targets across the set sizes, the lifeguards in the current study improve their active target detection from set size 3 to set size 6 by 10% (89% vs. 99% respectively).

In set size 9, their responses to targets are reduced by over 20% from set size 6 (99% for set size 6 vs 77% for set size 9).

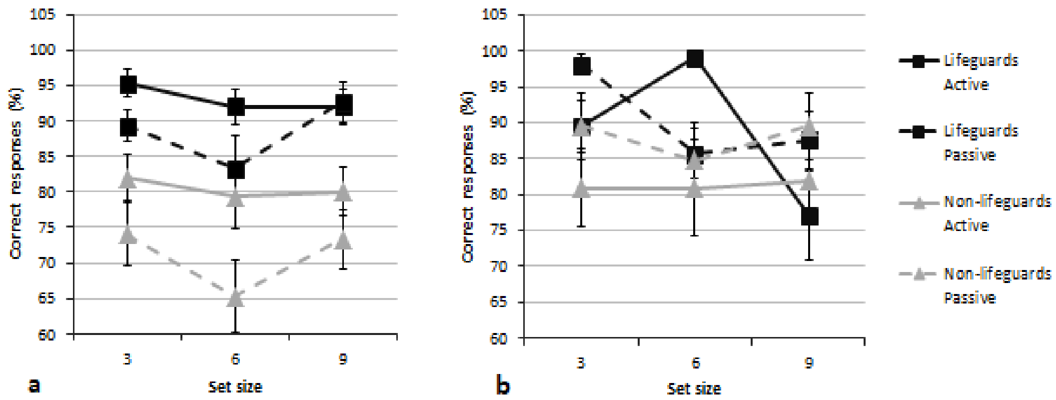


Figure 13. Correct responses to drowning targets across the 3 conditions for (a) Laxton & Crundall (2018) and (b) PhD Experiment 1

The similar methodologies of the Laxton and Crundall (2018) study and Experiment 1 allowed the accuracy rates to be compared across the two experiments. When these data were subjected to a 2 x 2 x 2 ANOVA (experiment x group x drowning type), the interaction between group and experiment did not reach conventional levels of significance ($F(1,98) = 2.8$, $MSe = 409.2$, $p = 0.095$), though the interaction between drowning type and experiment was significant ($F(1,49) = 17.65$, $MSe = 104.0$, $p < 0.001$). While the three-way interaction did not confirm that the non-lifeguard group was solely responsible for this change between the two studies, the mean values suggest that the increase in passive target accuracy across the two studies was primarily due to the improvement across the non-lifeguard groups.

Why might non-lifeguard participants be better at spotting passive targets in the current study compared to that of Laxton and Crundall (2018)? There are a number of possibilities: First, the current study differs slightly in design to the previous one. In the Laxton and Crundall (2018) experiment, participants were only allowed to make a single response which then terminated the video playback. The non-lifeguards were over-represented in terms of the number of premature responses in the 2018 study, having incorrectly terminated the clip on 17.3% of all trials, while the lifeguards made premature responses on only 7.7% of all trials. Furthermore, premature responses were more prevalent on passive, rather than active trials (15.1% vs. 9.9%). This suggests the passive drowning targets may not have been fairly represented in the previous study. In contrast, participants in the current study could make multiple responses in a single clip, allowing them the opportunity to detect all targets. This may have influenced the higher accuracy of non-lifeguard participants, particularly to passive targets.

A second possible explanation for the improved performance of non-lifeguard participants in detecting passive targets may be due to a further difference between the two studies. In an effort to better prepare the participants for the task, the current study gave descriptions of the two drowning types. Laxton and Crundall (2018) did not do this, which may have increased the salience of active drowning over and above that of passive drownings, at least in the non-lifeguard group who may have only expected to see active drownings (perhaps because this type of drowning is more prevalent in television and film). By providing a description of passive drowning in the current study, the non-lifeguard participants may have become more sensitised to the lack of movement characterising passive targets, rather than simply searching for an increase in activity to denote a target.

A third possibility is that even the lifeguards found the trials with nine swimmers too demanding. This is supported by the interaction between set size and experience, where lifeguards were only found to outperform the non-lifeguard participants at the small and intermediate set sizes. Once set size increased to nine swimmers, accuracy between lifeguards and non-lifeguards became comparable. This decreased accuracy at set size nine was not seen in Laxton and Crundall's (2018) study.

Why might the lifeguards' superiority for responses be reduced in the largest sets size in the current study? One possibility is that changes in the study design resulted in changes in the participants scanning behaviour. In Laxton and Crundall's study, participants were given feedback after each trial, whereas the participants in the current study were not. Providing feedback may have reinforced successful search strategies, with participants changing strategies over the different set sizes. However, in the current study, participants may have stuck to one strategy, which in the low and intermediate set size is successful, but is less successful in the higher set size. For instance, a serial search may be effective with 3 or 6 swimmers, but may become less useful with 9 swimmers. Response times suggest that lifeguards still respond more quickly than non-lifeguards in this condition, but if they are simply trying to speed up a serial search, they may miss some drownings altogether.

It is also possible that the lifeguards are able to use their experience to chunk visual information, which is effective for the smaller set sizes and difficult when there are 9 swimmers. When there are only 3 swimmers in the pool, it is possible that the lifeguards are able to employ a strategy where they can process the three swimmers of the smallest set size faster than non-lifeguards. This is potentially done by looking in the spaces between nearby swimmers, which may increase their chances of spotting a drowning swimmer before the clip ends. This has been demonstrated in previous research, where expert searchers process more visual information in a scene by chunking items that are located in close proximity (Reingold et al., 2002). When the search array increases to nine swimmers, a chunking strategy may become less useful, with more items creating a visually cluttered space. When looking at the pool it might also be expected that with only three swimmers in the pool, the drowning swimmer would be fixated more often than when there are nine swimmers in the pool. However, the results demonstrate that targets in set-size 3 received fewer fixations. If lifeguards are chunking swimmers in the smaller set sizes, just like the expert chess players in Reingold et al. (2002) study, then it is possible that the lifeguards are actively fixating locations in-between swimmers in order to attend to all elements of the chunk through parafoveal vision.

The breakdown in detection performance in the higher set size may also be a result of a limited tracking ability. In multiple object tracking (MOT) research, where observers typically track a subset of moving objects within a display for several seconds, it has been found that this tracking is limited to around 4 items (Cavanagh & Alvarez, 2005; Pylyshyn & Storm, 1988). This capacity to track multiple objects has been found to be further limited when observers are being asked to track events rather than objects, with observers limited to two or three items (Wu & Wolfe, 2016). It is possible that the lifeguards in this study are able to passively track the three swimmers in the smallest set size, resulting in the better performance. However, when there are more swimmers in the pool, participants may not be able to track the swimmers and instead rely on looking at individual swimmers more often, hence the targets in the higher set size being missed more often, despite receiving more fixations. These possibilities are only speculative; once more research has been conducted and these findings have been replicated, we may then begin to understand these subtle effects.

The influence of set size was also found in the responses to the different drowning targets. Passive drowning targets in the lowest set size are correctly responded to more often and elicit the fastest responses. This may be a result of the passive drowning targets being more salient in the lower set sizes, but also a result of them being highly informative once detected. Searchers may be able to detect the drowning swimmer faster in the search due to someone face down and motionless in the water being maximally different to the two other people swimming. It would be expected that this pop-out effect would be greater when there are more distractor items that are maximally different (Treisman & Gelade, 1980). However, in these dynamic scenes the difference between the motionless target and the moving distractors may be reduced, with the motionless target becoming lost in the increased number of moving distractors.

The passive drowning behaviour also offers enough information for searchers to make a rapid decision on the presence of the target once it has been fixated. This is reflected in the number of targets fixated, with participants responding to a similar number of targets as they fixated for passive drownings (91.9% fixated, 93.8% detected). Conversely, participants responded to fewer of the active targets than they actually fixated during the drowning window (92.8% fixated, 85.2% detected), indicative of *'Look but fail to see'* errors (Hill, 1980; Koustanai et al., 2008). This reduced accuracy in the detection of active targets in the lower set sizes differs from the findings of Laxton and Crundall, who found overall active targets were detected more often. However, this difference may be related to the aforementioned modifications to the experimental design.

At certain levels of the set-size factor active drownings are also responded to less. This may result from the targets being less salient, with certain behaviours of the instinctive drowning response sharing features with actions of other swimmers. For example, the flailing arms of a drowning target may be considered similar to a front crawl or butterfly arm motion. Similarly, the submergence and re-emergence of a struggling swimmer's head may be mistaken for a breathing technique. This would be consistent with research suggesting search difficulty when targets and distractors share similar properties (Alexander & Zelinsky, 2011; Neider, Boot & Kramer, 2010). Once detected, these active drownings may then need to be considered to see if the behaviours present are representative of a drowning swimmer. Overall, active targets received longer average fixation times compared with passive targets, and had longer between being first fixated and time to respond compared to passive drownings, which shows supporting this interpretation.

Interestingly no differences were found between participant groups in the eye tracking data. Both participant groups appear to scan the scene similarly, and thus fixate the drowning victim at a similar point in time, but then the non-lifeguards do not appear to recognise the outward characteristics of the drowning (resulting in the differences between groups in terms of their behavioural responses). This suggests that scanning patterns are less important in distinguishing between experts and novices in lifesaving visual search compared to the identification of the drowning characteristics once targets have been fixated. It should be noted that some marginal differences between experience groups may have become significant if there had been a greater number of participant in both groups, particularly for the eye-movement measures such as time to first fixate the target, where the difference between the two experience groups was greater than 300 ms. However, due to the difficult nature of recruiting the expert group, larger samples would not have been practical in this project.

It is possible that increased distraction from a greater number of distractors offsets this benefit in the largest set size. This may be due to *crowding* – the inability to identify objects due to the proximity and density of clutter in the visual scene. Importantly, crowding is considered to affect the processing and discrimination of a target object, rather than detection (Whitney & Levi, 2011). This is demonstrated in previous exploration into lifeguard scanning behaviours, with suggestions that increased numbers of swimmers in the pool creates a crowding effect and not all swimmers can be attended to (Lanagan-Lietzel et al., 2015). A novel way to test whether drowning characteristics are the factor that leads to lifeguard superior performance would be to include a test group of *lifesavers*. Lifesavers are a group of people with a self-selected interest in lifesaving skills. They are often people who partake in recreational clubs and competitions, learning and practicing rescue techniques. They would be familiar with drowning characteristics, but, crucially, are not explicitly trained in how to scan pools (as lifeguards are). If lifesavers were to be found better than non-lifeguard participants, this could support the notion that exposure to drowning characteristics results in lifeguard/lifesaver superiority, rather than explicit training in search techniques (which only lifeguards receive).

As set size increases to 9 swimmers it appears that searchers are becoming affected by the increase of the number of background swimmers. This is potentially a result of participants employing one strategy for all set sizes; however, when there are more swimmers in the pool this strategy becomes less effective. For instance, if participants are using a chunking strategy, drowning targets may be detected relatively easily in the lower set sizes as the search array is sparser, with fewer distractors to occlude and camouflage the target. However, once the search array becomes more crowded and cluttered with the increase of more swimmers, chunking of information becomes more difficult with more items to explore, especially as their status (from non-target to target) can change at any point. These searches may be fast with more of the targets being fixated, but there is a possibility that not all items are being processed.

It is odd that lifeguards' search breakdowns at set size 9, given that they are used to lifeguarding much busier pools. Laxton and Crundall (2018) did not find this in their study, where lifeguards did seem to change strategy. It may be interesting to explore this further in yet larger set sizes. While the current approach explores lifeguard search skills in a controlled environment, lifeguards are required to supervise much busier pools, therefore it may be more realistic to consider the effects of a cluttered pool on visual search. This may be particularly interesting for active drowning conditions when background swimmers are engaging in fun swimming, where features may overlap to a greater extent. For example the submergence and re-emergence of the *instinctive drowning response* (Pia, 1974) may have greater overlap with the characteristics of swimmers who are just playing in the water, perhaps jumping off the bottom of the pool. Similarly, passive drownings may overlap with swimmers who may simply float face-down on the surface.

To unpack where the differences in drowning detection lie between experience level (if it is a result of recognising the characteristics of drowning swimmers or in search skills) a second study was conducted with a wider range of lifeguarding/lifesaving experience. This second study also provided an opportunity to test the impact of providing instructions regarding the different drowning types (to assess whether this information is the cause of the improved responses of the non-lifeguards in this experiment compared to Laxton and Crundall, 2018).

3.5 Experiment 2

The effect of expertise in visual search is well documented (Stainer et al., 2013, Laxton & Crundall, 2018). Experiment 1 has shown superiority of lifeguard search in low and intermediate set sizes for accuracy of responses and across all set sizes for response times. However, more research is needed to understand where the differences in the superior search of lifeguards lie. Therefore, Experiment 2 aimed to explore any experience difference between four distinct groups of participants: lifeguard trainers, lifeguards, lifesavers and non-lifeguards. Lifesavers are individuals who attend recreational clubs where they train to help someone in distress in the water. However, they are not trained to scan for such behaviours, and whilst a lifeguard has a duty of care, the lifesavers main priority is their own safety. It is expected that these lifesavers will have better detection of drowning swimmers than the non-lifeguards, as their interest in lifesaving will lead to them being able to recognise the signs of drowning. However, it is also expected that, if the additional training lifeguards receive (e.g. instruction on the 10:20 scanning method) is relevant to the current task, their detection of drowning swimmers will be better than that of the lifesavers.

In addition, this second experiment will also explore the effect of information of drowning characteristics given prior to the experiment. It is possible that changes in instructions given to participants in Experiment 1 compared to the instructions used in Laxton and Crundall (2018) may account for differences in the detection of active and passive drownings in the two experiments. It is expected that the information given will provide participants with some training on the characteristics of drowning, thus shaping performance on the task.

Finally, this study was designed to run from a laptop, using touch screen technology to identify drowning targets, while still allowing for multiple responses. The introduction of a scoring window that includes both spatial and temporal limits is an improvement over the purely temporal scoring window in

Experiment 1; the previous method may have incorrectly considered responses to be hits when a participant was actually responding to a non-target that coincidentally fell within in the temporal scoring window. It is expected that this new design will better distinguish the difference between non-lifeguard and lifeguard responses to the drowning swimmers, with participants needing to locate and respond to the drowning swimmer. Furthermore, the multiple participant groups will allow a greater understanding of what level of expertise is required to produce a superiority effect.

3.6 Method

3.6.1 Participants

One hundred and nineteen participants were recruited to take part in this study (with a mean age of 24.74, SD = 11.36, 68 female). Forty-two of these participants had completed necessary qualifications in lifeguarding prior to testing. The mean age of these lifeguard participants was 23.24 (SD = 9.03, 16-54 age range, 17 female). These participants formed our *lifeguard* participant group. Forty of the participants had no lifeguarding or lifesaving experience. This *non-lifeguard* group had a mean age of 23.7 (SD = 8.8, 16-50 age range, 30 female). A further 26 participants were members of a lifesaving club, who have not completed any lifeguarding qualifications. This *lifesaving* group had a mean age 25.5 (SD = 17.06, 16-72 age range, 14 female). Finally, eleven participants formed our lifeguard *trainer* group, with a mean age of 32.4 (SD = 8.87, age range of 20-45, 7 female). Lifeguard, lifesavers, and trainers were recruited from local pools and a lifesaving national competition. The non-lifeguards were an opportunistic sample from the U.K. Participants came from a range of educational backgrounds, ranging from GCSEs (U.K. school leaver qualification) to Doctoral qualifications.

3.6.2 Design

A 2 x 4 x 2 x 3 design was employed, comparing study information (informed vs. non-informed in regard to drowning characteristics), experience group (trainers, lifeguards, lifesavers, and non-lifeguards), drowning type (15 active drowning trials and 15 passive drowning trials), and set size (3, 6, or 9 swimmers). In the informed condition, half the participants were told that the drownings could be either passive or active, and what behaviours might characterise these targets, whilst the other half of the participants were only told that a drowning may occur. The rest of the design was the same as that used in Experiment 1, except for 2 modifications. First, participants could make multiple responses *until* a correct response was made (which would result in termination of the clip). A feedback screen was then shown before moving on to the next clip. The second modification was to include localised responses via a touchscreen, with the location coordinates for each response recorded. Rather than pressing a button to acknowledge a drowning target, as in Experiment 1, participants in Experiment 2 were required to touch the area of the laptop screen to identify a target. A responsive window was placed around the drowning target, which covered an area measuring 250 x 140 pixels, in the horizontal and vertical axes respectively. This spatial window around the target accounted for 0.8% of the total screen area. The responsive window was only active after the onset of the drowning and moved with the drowning victim. Each time a new response was made in a single clip the reaction time and the coordinates would be updated in the response output log, therefore a clip would terminate after a correct response to log participants' first response after drowning onset. If a response was made after drowning onset but was not within the response window an incorrect response was logged. An incorrect response was also recorded if a response was made during a no-drowning trial. The experiment was created to run as a single, continuous, randomised block with a fixation screen before each trial and feedback screens after each clip.

3.6.3 Apparatus and stimuli

The stimuli were the same as those used in the first experiment. However, there was an addition of AOIs added to them, creating the responsive window around the drowning swimmer. The AOIs were not visible to the participants. In total there were 45 clips, and these were randomised within a single block. The clips involved 15 active drownings, 15 passive drownings and 15 catch trials, where there were no instances of drowning. For each drowning condition there was five clips with 3 swimmers, five with 6 swimmers and five clips with 9 swimmers. Before the presentation of each clip a central fixation cross appeared for 500 ms. After each clip a feedback screen was presented. If a correct response was registered, with either a correct identification of a drowning swimmer or a 'no response' being made to drowning absent trial, then a 'correct' feedback was given. If an incorrect response was given identifying a wrong location or a response given during a drowning absent trial, then 'incorrect' feedback was given.

While the first experiment employed the use of eye tracking technology and had participants make button responses, this second experiment used a touch screen laptop with participants able to tap the screen in the location of the drowning swimmer. The experiment was created in Psychopy, using Python coding and presented on a Lenova Yoga laptop, with a screen resolution 2880x1620.

3.6.4 Procedure

To recruit lifeguards, the experimenter arranged testing at local pools and at a national lifeguard competition. The test was conducted in convenient locations, such as in a canteen area or in the poolside viewing area. Non-lifeguard participants were tested in similar conditions, using a common area with the Psychology department (to ensure similar levels of distractibility). Participants were first asked to fill in a consent form and given instructions for the task. The participants were split into one of two conditions at this point; informed (told about the different drownings they would see and the typical behavioural characteristics of each drowning) and non-informed (who were simply told a drowning may occur). They were then told to touch the screen of the laptop, which would take them to a short demographic questionnaire. Before the main experiment began, participants were given a practice with the touch screen. This required them to touch all the green circles and ignore the red circles. This then moved automatically to the practice trial. The practice trial did not contain a drowning, therefore did not require the participants to respond. Participants were told to only touch the area of the screen where the drowning swimmer was located when they detected a drowning incident. A fixation cross was presented first for 500 ms, followed by the video clip. After the video, participants were presented with correct or incorrect feedback for the practice trial and told there was no drowning; they then started the main experiment, which followed the same format. After completion of the main block, participants were thanked for their time and fully debriefed. This experiment was conducted with approval from the University's ethical board and run in accordance with the British Psychological Guidelines.

3.7 Results

3.7.1 Behavioural data

3.7.1.1 Catch trial responses

Before analysing the accuracy to the drowning trials, the response rate to the non-drowning trials was assessed. A catch trial was recorded as incorrect if a response was made. Catch trial responses were subjected to an experience group x study information x set size (4 x 2 x 3) mixed ANOVA. The only main effect to reach significance was that of the experience group ($F(3,111) = 3.8$, $MSe = 369.7$, $p < 0.05$, $\eta_p^2 = 0.09$). On average the non-lifeguards responded incorrectly to catch trials the most (27.3%), while lifesavers (19.0%), lifeguards (14.8%), and lifeguard trainers (10.9%) made fewer false alarms. Post hoc Bonferroni t-tests reveal that the non-lifeguards differed from the lifeguards ($t(80) = 2.82$, $p < 0.008$). Lifeguards and trainers were not significantly different in their incorrect responses to catch trials, nor were lifesavers from all other groups.

3.7.1.2 Signal detection analysis

Measures of d' and c were calculated for each participant. These were subjected to a similar experience group x study information x set size (4 x 2 x 3) mixed ANOVA. The main effect for d' to reach significance was that of experience group ($F(3,115) = 9.61$, $MSe = 0.64$, $p < 0.001$, $\eta_p^2 = 0.2$). On average the non-lifeguards' sensitivity to targets was lowest (2.02), while lifesavers (2.59), lifeguards (2.87), and trainers (3.06) were more sensitive to drowning targets. Post-hoc Bonferroni-corrected t-tests revealed that the non-lifeguards differed from both the lifeguards ($t(80) = -4.59$, $p < 0.001$) and the trainers ($t(49) = -3.58$, $p < 0.008$). No other differences between the groups were noted. This suggests that the non-lifeguards had a lower rate of detecting the target than the lifeguards and the lifeguard trainers.

The measure of c revealed a main effect of experience group ($F(3,115) = 11.17$, $MSe = 0.68$, $p < 0.001$, $\eta_p^2 = 0.2$). On average non-lifeguards' criterion value to targets was -1.45, the lifesavers -1.98, the lifeguards -2.39 and the trainers -2.64, suggesting that participants with less experience are less conservative when judging someone to be drowning. Post hoc Bonferroni corrected t-tests noted that the non-lifeguards differed to both the lifeguards ($t(80) = 5.06$, $p < 0.001$) and the lifeguard trainers ($t(49) = 4.49$, $p < 0.001$). No other differences were noted between the groups.

3.7.1.3 Behavioural responses

First, the percentages of trials with a drowning target that were correctly responded to were analysed. Trials with a drowning target were considered incorrectly responded to if a response was made before the onset of a drowning, if no response was made, or if a response was made after onset in an incorrect location (we only recorded 12 incorrect location responses from 9 non-lifeguards – 0.3% of all total trials across all participants). The remaining trials were subjected to a study information x experience group x drowning type x set size (2 x 4 x 2 x 3) mixed ANOVA.

The main effect for the study information was not significant ($F(1,111) = 0.35$, $MSe = 39.8$, $p = 0.55$, $\eta_p^2 = .00$). A main effect was noted for experience group ($F(3,111) = 1.5$, $MSe = 238.7$, $p < 0.001$, $\eta_p^2 = 0.22$). Post hoc Bonferroni corrected t-tests revealed that lifesavers detected more targets than the non–lifeguards ($t(64) = -3.22$, $p < 0.0083$), but there was no difference between the accuracy of the lifesavers and lifeguards ($t(66) = -1.01$, $p = 0.32$), or between the lifeguards and trainers ($t(51) = 0.28$, $p = 0.78$) (87.6% non-lifeguards, 93.8% lifesavers, 94.9% lifeguards & 94.5% trainers). The remaining two effects did not reach significance.

An interaction between set size and drowning type reached significance ($F(2,222) = 11.5$, $MSe = 118.5$, $p < 0.001$, $\eta_p^2 = 0.09$). Planned repeated contrasts revealed that the interaction is driven by responses made between set size 3 and 6 ($F(1,111) = 25.1$, $MSe = 205.1$, $p < 0.001$, $\eta_p^2 = 0.18$). Figure 14 shows that this may be driven by the active drowning responses improving at set size 6 and passive responses deteriorating at set size 6. Post hoc Bonferroni adjusted t-tests support this, revealing a difference between the responses at set size 3 and at set size 6 in the active drowning trials ($t(118) = -3.7$, $p < 0.001$) with drownings in an array of 6 swimmers being identified more often (95.8% for 6 swimmers and 90.7% for 3 swimmers). The change between 3 and 6 swimmers in passive drowning trials also proved to be significant ($t(118) = 3.5$, $p < 0.007$), with drowning trials with 3 swimmers being identified more often (95.5% for 3 swimmers and 90.3% for 6 swimmers). Differences were also found between active and passive drownings in set size 3 ($t(118) = -3.2$, $p < 0.007$) and between active and passive drownings at set size 6 ($t(118) = 3.9$, p < 001). Passive drownings were detected more often in set size 3 (90.7% active & 95.4% passive) and active drownings were identified more in set size 6 (95.8% active & 90.2% passive).

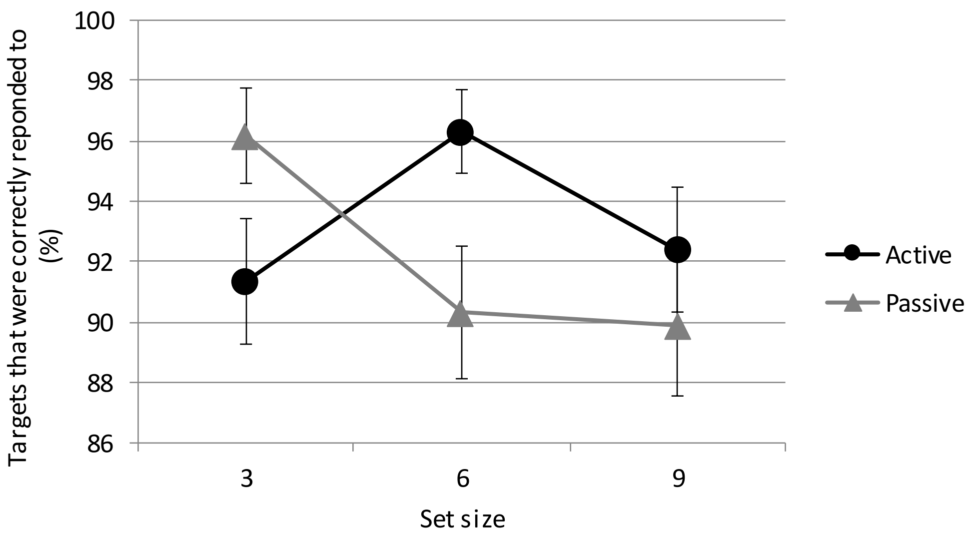


Figure 14. The mean percentages of trials containing drowning targets that were accurately responded to (with standard error bars)

Response times to correctly identified targets were also subjected to a similar 4 x 2 x 2 x 3 ANOVA. The main effect of experience group was significant ($F(3,111) = 1.0$, MSe = 4479735, $p < 0.001$, $\eta_p^2 = 0.17$), a difference was noted in the mean scores between the four experience groups (non-lifeguards: 5033 ms; lifesavers: 4656 ms; lifeguards; 4086; trainers: 4026). However, post hoc Bonferroni corrected t-tests do not quite show this effect; there was no difference between the non-lifeguards and the lifesavers ($t(64) = 1.49$, $p = 0.14$), lifeguards were 600 ms faster than lifesavers ($t(66) = 3.46$, $p < 0.001$), and there was no difference between lifeguards and trainers ($t(51) = 0.25$, $p = 0.80$).

The main effect of drowning type ($F(1,111) = 26.5$, MSe = 1597504, $p < 0.001$, $\eta_p^2 = 0.19$) revealed that active drownings were responded to more slowly than passive drownings (4729 ms vs. 4172 ms). The main effect of set size ($F(2,222) = 9.8$, MSe = 1268107, $p < 0.001$, $\eta_p^2 = 0.05$) was subjected to planned repeated contrasts which noted that set size 3 produced faster responses than set size 6 ($F(1,111) = 17.2$, MSe = 2219662, $p < 0.001$, $\eta_p^2 = 0.14$). However, there was no difference between set size 6 and set size 9 ($F(1,111) = 0.01$, MSe = 2793379, $p = 0.94$, $\eta_p^2 = 0.00$) (with means of 4219 ms, 4647 ms, and 4728 ms respectively).

The main effect of study information did not reach statistical significance.

Three interactions were significant, with three 2-way interactions (set size x group, drowning type x group, and drowning type x set size) subsumed by the significant 3-way interaction between experience group x drowning type x set size ($F(6,222) = 3.32$, MSe = 1021527, $p < 0.05$, $\eta_p^2 = 0.08$) (see Figure 15). First, it is clear that the set size effect is more modest in the passive condition, with set size 9 producing an ostensibly greater delay than set size 6. In contrast, a delay is noted in set size 6 of the active trials, at least for the non-lifeguards.

Furthermore, the active drownings provide the greater differentiations between the experience groups, especially at the higher set sizes.

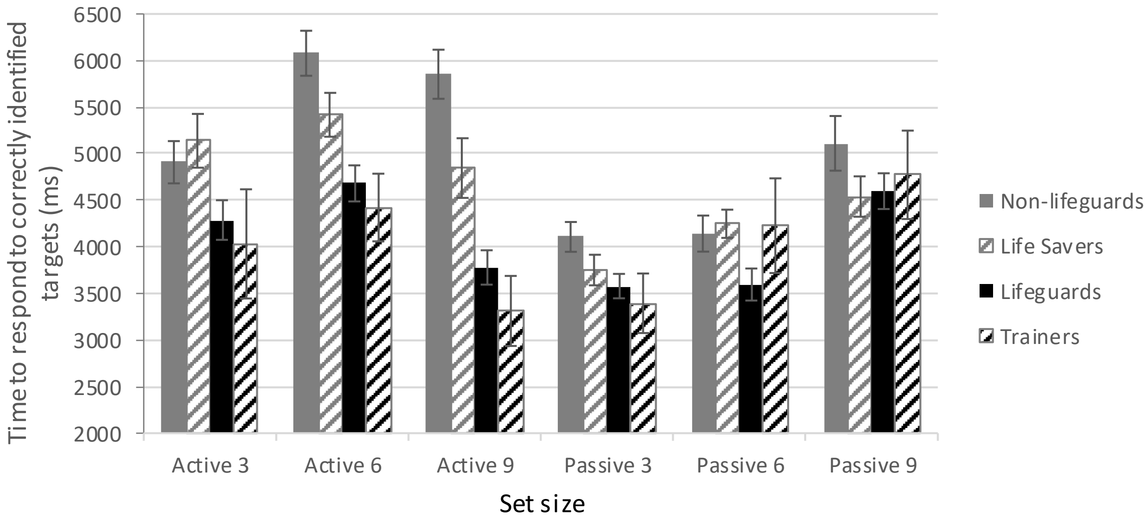


Figure 15. The mean responses times of correctly responded to trials (with standard error bars)

To make a comparison back to Experiment 1, the analysis was rerun, dropping the (non-significant) study information variable and removing the lifesaver and trainer groups. This resultant experience group x drowning type x set size ANOVA revealed the same pattern of significance: lifeguards are still found to detect drowning swimmers faster than non-lifeguards ($F(1,80) = 26.1$, $MSe = 1475543$, $p < 0.001$, $\eta_p^2 = 0.25$), echoing the results of Experiment 1. Passive drownings were detected faster than active drownings ($F(1,80) = 47.3$, $MSe = 1476540$, $p < 0.001$, $\eta_p^2 = 0.37$). The main effect of set size ($F(2,160) = 11.7$, $MSe = 1424366$, $p < 0.001$, $\eta_p^2 = 0.13$), when subjected to planned repeated contrasts revealed that only set size 3 differed from set size 6 ($F(1,80) = 11.3$, $MSe = 2581688$, $p < 0.001$, $\eta_p^2 = 0.12$), but set size 6 did not differ from set size 9, again similar to Experiment 1. The three 2-way interactions were again subsumed by the 3-way interaction ($F(2,160) = 5.6$, $MSe = 981913$, $p < 0.05$, $\eta_p^2 = 0.07$). As can be seen in Figure 16 this appears to be driven by the response times of non-lifeguard participants being most adversely affected by an increase between set size 3 and 6, and the lifeguard responses becoming faster between set sizes 6 and 9. However these effects are only apparent when faced with active drowning trials.

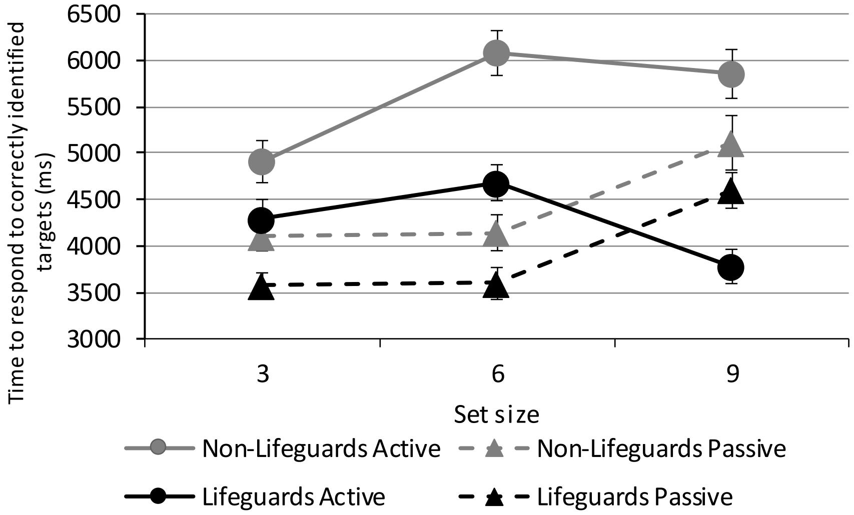


Figure 16. Average reaction times to correctly responded to trials for lifeguards and non-lifeguards (with standard error bars)

To assess this interpretation, separate drowning type x set size ANOVAs were conducted for each experience group. A number of differences between the two groups become apparent, which help unpack the three-way interaction. First, the main effect of set size (with set size 3 producing faster responses than set size 6, but no difference between set size 6 and 9) is only evident for the non-lifeguard group. Second, while both groups show a significant interaction between drowning type and set size, the effect size for the interaction is greater for the non-lifeguard participants ($F(2,78) = 10.6$, $MSe = 1017563$, $p < 0.001$) than the lifeguards ($F(2, 82) = 22.5$, $MSe = 948003$, $p < 0.001$) (η_p^2 : 0.21 vs 0.04). This reflects the degradation in response times that non-lifeguards demonstrated with active drowning targets when the set size increased to 6. Finally, a narrowing of the response time gap between drowning types is noted for both non-lifeguards and lifeguards when set size increases to 9 potential targets. This effect is stronger in the lifeguard group (η_p^2 = 0.46) than in the non-lifeguard group (η_p^2 = 0.26). This effect is seen to produce a cross-over interaction component for the lifeguard group. These RT interaction effects mirror those found in the earlier Laxton and Crundall (2018) experiment.

3.7.2 Regression analysis

A multiple regression to predict the accuracy of drowning detection was performed for all participants, with age, gender, highest level of completed education and lifeguarding experience as the predictors. The overall model was significant ($F(4,114) = 2.45$, $p = 0.05$, $R^2 = 0.28$). The means and SDs for each variable can be seen in Table 9.

Table 9. The means and SDs of the dependant variable and the predator values and the correlation matrix for the ccuracy of responses.

Variable	Mean	Sd	1.	2.	3.	4.	5.
1. Accuracy	90.90%	8.29	1				
2. Experience group	2.20	1.01	.257*	1			
3. Age	24.74	11.36	-.002	.109	1		
4. Gender	1.43	0.50	.125	.214*	-.058	1	
5. Education	2.31	0.92	.097	.041	.031	.040	1

Experience: non-lifeguard: 1, Life saver: 2, Lifeguard: 3, Trainer: 4
Education: GSCE:1, Alevel: 2, Undergraduate: 3, Master's:4, PhD: 5
Notes: *P < 0.05

An analysis of the unstandardized coefficients showed that experience (Beta = 1.98, $p < 0.05$) was the only significant predictor of drowning detection (see

Table 10). The standardised coefficients showed that experience group (Beta = 0.24) had a positive association with drowning detection, thus more experience was associated with better detection of the drowning swimmer.

Table 10. Summary of simple regression analyses for variables predicting drowning detection accuracy and reponse times to drowning detection.

Variable	*Drowning Detection Accuracy*			*Response times*		
	B	*SE B*	*β*	**B**	*SE B*	*β*
Constant	83.62	3.47		5536.81	373.75	
Experience group	1.98	.76	.24*	-347.78	81.67	-.38**
Age	-.02	.07	-.03	-1.36	7.13	-.02
Gender	1.15	1.54	.07	-89.97	165.82	-.05
Education	.76	.81	.09	-46.55	87.46	-.05

Notes: *P < 0.05, **P < 0.001

A similar regression was performed with the same predictor variables and with response times as the outcome variable. The mean response time was 4501 ms with a standard deviation of 933 ms. The correlations for the variables can be seen in Table 8. There was a good fit between the predictor variables and the dependent variable (multiple R = 0.16) with the adjusted R^2 showing that the predictor variables explained 13% of the variance in the accuracy of detection of the drowning swimmer. The overall relationship was significant ($F(4,114) = 5.35$, $p < 0.05$).

Table 10. Correlation matrix for the predictor and outcome variables for the response times.

VARIABLE	1.	2.	3.	4.	5.
1. RTS	1				
2. EXPERIENCE GROUP	-.392 *	1			
3. AGE	-.056	.109	1		
4. GENDER	-.130	.214*	-.058	1	
5. EDUCATION	-.064	.041	.031	.040	1

Notes: *P < 0.05, **P < 0.001

An analysis of the unstandardized coefficients showed that experience (Beta = -347.78, $p < 0.01$) was the only significant predictor of drowning detection. The standardised coefficients showed that experience (Beta = -0.38) had a negative association with time to drowning detection, however this negative association showed that more experience was associated with faster responses to detect the drowning swimmer.

3.8 Comparison between Experiments 1 and 2

The similar methodologies Experiment 1 and 2 allowed the accuracy rates and responses times to be compared across the two experiments for the non-lifeguard participants and lifeguard participants. The overall accuracy of responses was calculated for each participant and then subjected to a 2 x 2 (experience x experiment) between samples ANOVA. A main effect of experience group ($F(1,120) = 10.68$, $MSe = 96.33$, $p < 0.05$, $\eta_p^2 = 0.08$) revealed that the lifeguards were more accurate in their responses to drowning targets than non-lifeguards (92.22% vs. 86.14% respectively). The main effect of experiment ($F(1,120) = 5.16$, $MSe= 96.33$, $P < 0.05$, $\eta_p^2 = 0.04$) demonstrated that participants in Experiment 2 responded to drownings more accurately than participants in Experiment 1 (91.29% vs. 87.06% respectively).

The lifeguards in Experiment 2 detected more drownings than non–lifeguards (94.92% vs. 87.67%) when compared to the lifeguards and non-lifeguards in Experiment 1 (89.52% vs. 84.60%), however the interaction between experience group and experiment was not significant ($F(1,120) = 0.39$, MSe = 96.33, $p = 0.53$, $\eta_p^2 = 0.00$).

The responses times were subjected to a similar 2 x 2 (experience x experiment) between samples ANOVA. A main effect of experience group ($F(1,119) = 21.15$, MSe = 816625, $p < 0.001$, $\eta_p^2 = 0.15$) revealed that the lifeguard participants responded to drowning targets faster than non-lifeguards (4096 ms vs. 4891 ms respectively). The main effect of experiment did not reach significance ($F(1,119) = 0.15$, MSe = 816625, $p = 0.70$, $\eta_p^2 = 0.00$). The interaction effect also failed to reach levels of significance ($F(1,119) = 0.87$, MSe = 816625, $p = 0.35$, $\eta_p^2 = 0.01$).

3.9 Discussion

The results of Experiment 2 have further confirmed the predicted superiority of lifeguard participants in both accuracy of responses and in the response times. The accuracy results of the untrained lifesavers were also noted to reach a similar level of accuracy as the lifeguard participants. One interpretation of this similarity between the accuracy results of untrained lifesavers and lifeguards is that the advantage of training is not necessarily apparent in knowing where to look during the visual search (10:20 scanning technique), but rather knowing what to look for (exposure to drowning characteristics). This conclusion is based on the assumption that lifesavers are exposed to drowning characteristics but are not formally trained in scanning techniques as lifeguards are.

Interestingly, the benefit of exposure to drowning characteristics that seems to drive the accuracy of the lifesavers' responses did not appear in their reaction times in terms of being a similar level as the lifeguards. While lifesavers were found to respond to drowning targets marginally quicker than non-lifeguards, the lifeguards were seen to respond to the targets 600 ms faster than lifesavers on average. The faster response times of the lifeguards suggest that they may have some underlying benefit alongside the experience and knowledge of drowning characteristics. This could be from underlying cognitive skills that improve response times from target identification. For example, lifeguards and trainers have hours of poolside experience of visual search and surveillance, which may have resulted in them being able to process the characteristics of drowning swimmers faster. However further research is needed to explore what these contributing cognitive skills may be.

In both Experiments 1 and 2, passive drownings have consistently been detected faster than active drownings, especially so in the lower set sizes. This finding may initially appear at odds with literature showing that several aspects of motion appear to attract attention (Franconeri & Simons, 2003) such as motion onset (Abrams & Christ, 2003) and abrupt changes in motion direction (Howard & Holcombe, 2010). One might therefore expect the movements associated with active drownings to have greater salience than passive drownings. Furthermore, it has been shown that search for a moving target amongst stationary distractors is more effective than search for a stationary target amongst moving distractors (Verghese & Pelli, 1992). However, there are two potential sources of explanation for the apparent superiority of search for passive over active drownings. First, the active drownings were not displayed in a pool of stationary distractors. Rather, distractors were swimmers moving across the pool in both directions and with reasonably predictable body movements. Search for a stationary target amongst moving distractors is facilitated by order or structure in the motion displayed by the distractor set (Royden, Wolfe & Klempen, 2001). Therefore, it appears that the relative orderliness of the back-and-forth motion of the distractor swimmers may have afforded sufficient advantage to the search for passive drownings than would otherwise have been the case. Second, the *instinctive drowning behaviour,* often displayed in active drownings, has some feature overlap with normal swimming behaviours. For example, active drownings and normal swimming both involve arms being lifted out of the water, submergence and re-emergence of the head, and associated splashing. The similarity between the active drowning behaviour and normal swimming behaviours may make the active drowning harder to identify. A passive drowning, conversely, is often characterised by someone floating face down in the water, and the absence of movement in such incidents is likely to be maximally different to the distractor swimmers in this study.

Similar results have been found in traditional laboratory studies exploring similarities between targets and distractors. It is well established that target-distractor similarity is used to guide search (Guest & Lamberts, 2011; Wolfe, 1994) and that this is easier when the target and distractors differ. Thus in this task, searching for passive drowning should be easier because of its low similarity to distractors. Importantly, although it is known that a target defined by a unique feature will "pop out" in abstract displays, in changing dynamic scenes such as those used here, such pop out effects might not occur for targets. It is likely that the passive drowner does not pop out as such; but that their low target-distractor similarity aids attentional capture as these similarity-based effects have been shown in studies using real world objects. As reported in Chapter 1, Alexander and Zelinsky (2012) manipulated target-distractor similarity of real world, static objects (teddy bears), showing that search was harder when more distractors shared features with targets. It should be noted that the distractors in Experiments 1 and 2 were regimented swimmers. In less formal swimming conditions, it is likely that face-down floating may be displayed by some non-drowning swimmers who are merely playing. This may reduce the detection advantages we have found for passive over active drownings.

It may also be possible that the participants in this study developed a strategy where they simply looked for the odd one out in the pool. Such a strategy could include searching for swimmers in the pool that were not making any meaningful forward progression or looking for someone not behaving like the other swimmers. Target-distractor similarity could also come into play here, particularly for the passive drowning swimmers that differ from the activity of the distractor swimmers. If all other swimmers are engaging in continued lap swimming, where they make meaningful movements through the water, then the motionless passive drowners may stand out to the searcher as the odd one out, resulting in the faster response times to passive drowning compared to active drownings noted in both Experiments 1 and 2. The shared feature overlap between active drowning swimmers and the distractor swimmers (arm motions, head submerging and re-emerging) may therefore require more scrutiny when making a decision on drowning presence, resulting in the slower response times in this condition compared to the passive drownings.

The comparison between the two studies revealed that the second experiment elicited more accurate responses than the first experiment. However, because of the localised responses required in Experiment 2 it would be expected that accuracy would decrease because participants need to make responses within the correct location and a specific time window. Why might the second study produce more accurate responses? One possibility is that the differences between the methodologies drove this effect. In Experiment 1, the entire clip was played to participants, regardless of responses. However, in Experiment 2, upon making a correct response the trial would terminate. It may be that in Experiment 2, participants who make a premature response would keep searching the pool for any other potential drownings. Whereas, in Experiment 1, participants do not have the instant feedback for a correct response, so if a premature response was made, participants may think they have responded to the drowning swimmer and be satisfied with that they have completed the task and do not continue with any subsequent search. This would fit with the satisfaction of search theory (Tuddenham, 1962, Cain et al., 2011), which suggests that searchers become satisfied with the meaning of the search once one potential target has been identified and terminates any further searches of the trial.

Furthermore, the interaction between experience and experiment was not found to be significant, although the means for accurate responses would suggest that the greater difference between lifeguards and non-lifeguards is produced in Experiment 2, which used localised touch screen responses. A potential reason why this interaction was not found to be significant may be a factor of participants in both experiments performing close to ceiling. If the experimental stimuli were to reflect a more complex swimming scene (e.g. pools with more swimmers or children play swimming rather than regimented lap swimmers) a greater difference between the two methodologies may be observed. It may be possible to explore this in future research, using footage for a real environment

3.10 Conclusions

In summary, the experiments in Chapter 3 have shown a number of things. First, they have demonstrated the superiority of lifeguard visual search, supporting the earlier research conducted by Laxton and Crundall (2018). This was found in the behavioural responses in Experiment 1 and in the differences found between the lifeguards, lifesavers and non-lifeguards in Experiment 2. In terms of the eye tracking data, no difference between lifeguard and non-lifeguards' eye-movements were found, suggesting that any advantages for lifeguard drowning detection in the current data are not a result of any scanning benefits. Differences between the two drowning types were also observed, with passive drownings being detected faster compared to the active drownings. Passive drownings were also detected more often, particularly in the lower set sizes. While lifeguards were found to be superior in their detection of drowning swimmers in these simulated drowning conditions, more research is needed to explore if this better search performance carries over into detecting drowning events in a real scene. This will be explored in Chapter 4, using CCTV footage of a real swimming pool during peak holiday fun swim times.

Chapter 4
Search for a real drowning swimmer in a highly complex dynamic visual search task

The two experiments in Chapter 3 explored lifeguard visual search using simulated drownings and low levels of swimmers in the pool. While the results show advantages in drowning detection for lifeguard participants, it might be argued that the highly controlled stimuli, with low numbers of swimmers and regimented lap swimming creates an environment that is easier for the lifeguards to detect the drowning targets. It is also possible that the simulated nature of drownings may have favoured lifeguards, who are often exposed to simulated drownings.

The experiments in this chapter aim to explore if lifeguard superiority, which was found in the highly-controlled tasks of Chapter 3, translates to the detection of a drowning event in a real environment. Therefore, Chapter 4 investigated the visual search skills of lifeguards and non-lifeguards to real footage of drowning events caught on CCTV in an outdoor wave pool. In these scenes there is greater overlap between drowning behaviours (flailing arms, submergence and re-appearance, vertical position) and fun swimming behaviours (splashing, disappearing under the water, treading water), which may impact on the previously-noted differences in lifeguard and non-lifeguard drowning detection. These scenes also include a greater number of swimmers in the pool, which could also potentially affect the benefit of lifeguard experience on drowning detection.

This chapter will also explore different methodological approaches to testing lifeguard visual search. A naturalistic response time study will be used to explore behavioural responses and eye-movements in two studies, while a further study will use an occlusion approach, where the drowning event is occluded following drowning onset. The literature for occlusion-type detection tasks will be discussed.

The results of this study will help to provide further understanding of experience effects in lifeguard visual search and whether the benefits of experience previously noted transfer into naturalistic, dynamic stimuli. These studies will also provide evidence for the best approach to test lifeguards' visual search.

4.1 Introduction

As noted in earlier chapters, there is little explicit training and assessment for lifeguards in how to scan a pool environment for drowning events. One potentially negative impact of this limited training has been noted in prior research, with issues in target identification (Brener & Oostman, 2002; Herrmann & Roberton, 2017). There is also currently a lack of understanding of lifeguard visual search in the literature (Page et al., 2011; Lanagan-Leitzel, 2012; Lanagan-Leitzel & Moore, 2010).

Previous chapters have noted that there is some evidence for lifeguard superiority in drowning detection (Laxton & Crundall, 2017; Experiments 1 & 2). These studies benefited from highly controlled stimuli, where lifeguard drowning detection could be explored.

However, there are a number of problems with highly controlled stimuli that should be noted. First, the simulated drownings were acted by lifeguards, on the basis of what they expect to see (rather than what they might actually see) and may therefore provide unconscious benefits to lifeguard detection of drowning targets in the subsequent assessment. Second, there is a lack of variation in distractor and target behaviour, which may lead to drowning events being easier to detect. For example, the regimented swimming of distractors might increase the pop-out effect of drowning events. The behaviours of the regimented swimming of distractors may also create a search environment that is less relevant, with lap swimmers being less likely to get into trouble than children playing. One final problem comes from the limited number of distractor swimmers. This may have created a situation that was very easy to parse for the lifeguards.

It is possible that these problems with highly-controlled stimuli could be overcome with the use of naturalistic drownings. Such stimuli could be used to assess lifeguards' drowning detection abilities with real drowning characteristics, which would identify whether the highly controlled stimuli created a biased setting for the lifeguard participants. Furthermore, naturalistic poolside footage would create a realistic setting in terms of the number and behaviour of distractor swimmers.

There are a number of difficulties in obtaining naturalistic poolside and drowning footage. First, the infrequency of real drowning events does not make it feasible for the footage to be recorded by the experimenter. Additionally, there are issues with obtaining permissions to film real people in the swimming pool and ethical issues around filming or using film of genuinely distressing incidents. To overcome these difficulties real drowning video footage was sourced via the internet, with permission from the original uploader. These videos are of individual incidents filmed from an American wave pool, over a number of summers, with lots of different target incidents. While these events have been filmed over different days and over a number of years, there is only one camera location (with only minor variations in filming position), which provided some consistency over all clips. The main advantage of these real-event video clips is that they include high numbers of distractor swimmers, who are engaging in naturalistic play swimming behaviours. No drowning incident that has been captured on the video footage is particularly distressing, as only clips where the poolside lifeguards makes a successful rescue are used.

In the research presented in the next chapter, accuracy and response times were measured while lifeguard and non-lifeguards detected real distress incidents in the wave pool video clips. These pool scenes will include swimmers moving in random, un-controlled patterns and in a more complicated setting (greater overlap in drowning behaviours and 'fun' swimming behaviours; larger set sizes). Videoed footage of swimmers in a wave pool was used to investigate lifeguards' search skills in these different settings. The clips varied in set size, ranging from approximately 20 swimmers up to approximately 90 swimmers.

4.2 Experiment 3

Experiment 3 aimed to measure lifeguard responses to real drowning incidents in videoed footage of swimming pools. Accuracy of responses and time to respond to drowning incidents post-onset were both measured. Based on previous literature that has found lifeguard superiority (Laxton & Crundall, 2018) it was predicted that lifeguards would detect drownings more often and faster than non-lifeguards. Targets were chosen based on the response of an on-duty lifeguard jumping in to save them. It is also expected the as the number of swimmers in the pool increases from approximately 20 people to approximately 90 that both accuracy of drowning detection and response times would decrease, but lifeguards would remain superior in their responses compared to non-lifeguards.

4.3 Method

4.3.1 Participants

Fifty participants were recruited to take part in the visual search experiment (mean age 24.6, 28 female). Twenty-five of these participants (mean age 23.0, 12 female) had completed compulsory qualifications in lifeguarding prior to testing and had a varying amount of experience in poolside lifeguard duties (4.49 years of lifeguarding experience on average). The remaining twenty-five participants (mean age 26.3, 16 females) had no lifeguarding experience. Lifeguards were recruited from local leisure centres in the Leicestershire and Nottinghamshire areas. Non-lifeguard participants were an opportunistic sample from Nottingham Trent University, made up from a majority of postgraduate students and research assistants. Some participants were also recruited from the same leisure centre as the lifeguards (reception and gym staff).

4.3.2 Design

A 2 x 3 design was employed, comparing experience group (lifeguard vs. non-lifeguard) across set size (low vs. medium vs. high). There were 30 drowning present trials that contained active (conscious) drowning targets. These trials were genuine incidents, caught on a pool-side camera, which required lifeguard intervention. Active drowning targets were classed as swimmers who were displaying distress behaviours or the *instinctive drowning response* (Doyle & Webber 2016; Pia, 1974). In addition to the 30 drowning present trials, 15 non-drowning trials were also included. Of the 30 drowning present trials, ten trials contained low numbers of swimmers (averaging 29.4, range 23-36), ten trials contained medium numbers of swimmers (averaging 46.8, range 39-52), and the remaining ten trials contained high numbers of swimmers (averaging 73.2, range 60-89).

Accuracy and response times to detect the drowning target were recorded. Participants responded by making a touch-screen response on a laptop to indicate the location of a potential drowning incident. Participants were able to make multiple responses, however upon making a correct response, the clip would terminate. A feedback screen would then be shown, and the trial would then move onto the next clip. Correct responses were recorded if a response was made in the correct location on the screen and was made after drowning onset. Alternately, incorrect responses were recorded if no response was made in a drowning-present trial, a premature response that was not followed by a correct response was made, or an incorrect location after drowning onset was selected. It was not possible to respond too late to the drowning, as the clip ended abruptly following the drowning event. In addition to response times, the location coordinates for responses were recorded. Drowning onset of each clip was determined from the first signs of visible distress.

The experiment was created to run as a single, continuous, randomised block with feedback screens after each clip. A responsive window was placed around the drowning target, which covered an area measuring 250 x 140 pixels, in the horizontal and vertical axes respectively. This spatial window around the target accounted for 0.8% of the total screen area. The responsive window was only active after the onset of the drowning and remained centred on the target. If the target moved on the screen, the spatial response window moved accordingly so that accurate locations of participants' responses were recorded. During presentation to participants, all trials were randomised within a single block, and all participants viewed all trials.

Each time a new response was made in a single clip the reaction time and the coordinates would be updated in the response output log, therefore a clip would terminate after a correct response in order to log participants' first response after drowning onset. If a response was made after drowning onset, but was not within the spatial response window area, an incorrect response was logged. Before the presentation of each trial, a fixation cross was presented on the centre of the screen for 500ms.

4.3.3 Stimuli and Apparatus

Initial video footage, captured by a static poolside camera at an American wave pool, was accessed from YouTube with the uploader's permission to use for experimental stimuli[2]. "Wavepool lifeguard rescue" videos 1-42 were used in the experiment. The camera is stationed at the left-hand side of the pool at the deep end. The footage shows either a long shot of the pool, looking towards the shallow end or a zoomed in shot of just the deep end (see Figure 17). Big inflatable rubber rings can be seen in the pool as well as the swimmers.

Footage is completely naturalistic, with swimmers (mostly children) engaging in fun swim behaviour (e.g. chatting in a group with friends, riding on inflatable rings, swimming and playing). The drowning incidents are real swimmers in distress; however all video clips have a real lifeguard performing a rescue in a

[2] Footage can be found at https://www.youtube.com/channel/UCnERyC7dwJwTvEyzYz6uxHw.

timely manner (within the taught 10:20 second standard) and none of the rescued swimmers suffered any long term injury or distress from the incident. All distress incidents are either swimmers displaying the *instinctive drowning response* or weak swimmers showing obvious signs of distress and loss of floatation (Pia, 1974; Doyle & Webber, 2016). The drowning incidents were cut to the point in which the real pool lifeguard makes their response and enters the water.

Forty-five clips were selected from the footage, evenly distributed across the varying set size level. 15 clips contained no drowning incidents, with 5 in each set size condition. The clips varied in length, ranging between 9-35 seconds. Drownings occurred quasi-randomly within the trial, happening at some point after the first 5 seconds. The drowning incidents lasted between 2-19 seconds with clips ending immediately following the drowning. On average, drowning in the low set size last 6.95 seconds, drownings in the medium set size last an average of 5.58 seconds, and drowning in the high set size lasted an average of 6.11 seconds. A one-way ANOVA was used to explore the potential differences between the drowning lengths over the 3 set sizes, but none were found ($F(2,29) = 0.22$, $p = 0.8$).

Trials were played without an audio track to avoid the participants hearing early responses from the real pool lifeguard raising the alarm to the drowning situation. This also allowed the experimenter to focus on just visual skills.

The trials were run on a Yoga Lenova touch screen laptop, with a screen resolution of 2880 x 1620, running Psychopy. The trials were run in a randomised block, with a feedback screen after each trial. Participants could make localised responses on the touch screen of the laptop to indicate where a drowning incident was occurring. Spatial response windows (invisible to participants) were centred on the drowning target and recorded correct localised responses.

Figure 17. Four screen shots taken from video stimuli

4.3.4 Procedure

In order to recruit lifeguards, the experimenter arranged testing at local pools in Nottinghamshire and Leicestershire. The test was conducted in convenient locations within the pools, such as in a canteen area or in the poolside viewing area. Non-lifeguard participants were tested in similar conditions, using a common area of the university. Participants were first asked to fill in a consent form and were then given instructions for the task. Participants were told the nature of the study before starting, including that they may see some distressed swimmers and that video clips are of real pool footage. The participants were also made aware that they may withdraw at any point during the study if they did not wish to continue. Before the main experiment began, an on-screen demographic questionnaire, and a touch-screen practice test, was presented. For the touch-screen practice test, participants were asked to touch all green circles that appeared on the screen and ignore any red circles. Following this, a practice drowning trial was presented. The practice trial did not contain a drowning, therefore did not require the participants to respond. Participants were given correct or incorrect feedback for the practice trial and told there was no drowning. They then started the main experiment. All 45 trials were presented in a single, randomised block, with each clip preceded by a 500 ms fixation cross and followed by a feedback screen. After completion of the main block, participants were thanked for their time and fully debriefed. This experiment was conducted with approval from the University's ethical board and run in accordance with the British Psychological Guidelines.

4.4 Results

4.4.1 Behavioural data

4.4.1.1 Catch trial responses

The response rates to non-drowning trials were analysed first. Non-lifeguards incorrectly responsed to 21.1% of catch trials on average and lifeguards incorrectly responded to 28.8% of catch trials on average, but this difference was not significant ($t(48) = 1.39$, $p = 0.17$).

4.4.1.2 Signal detection analysis

The measures of *d'* and *c* were also calculated for each participant. These measures combined the hit rate for each participant across all drowning swimmers and compared them to the number of false alarms, where participants reported a drowning swimmer in catch trials.

An independent *t*-test compared these SDT measures across the two participant groups. There was no difference in the sensitivity to drowning swimmers between the lifeguards and non-lifeguards ($t(48) = -0.49$, $p = 0.625$), with *d'* of 1.45 and 1.35 respectively, suggesting that there was no difference between the participants likelihood to detect the target. There was no difference between the groups in terms of criterion values ($t(48) = 0.07$, $p = 0.945$), with criterion values of -0.80 for non-lifeguards and -0.82 for lifeguards, suggesting there is no difference between participants' likelihood to say 'yes' to the signal. .

4.4.1.3 Behavioural responses

The percentage of trials with a drowning target that received a correct response were then analysed. Trials with a drowning target were considered incorrectly responded to if no response was made following the onset of drowning activity or a response was made to an incorrect location. The trials that received correct responses were converted into percentages and subjected to a group x set size (2 x 3) mixed ANOVA.

The main effect of experience group ($F(1,48) = 12.2$, $MSe = 157.3$, $p < 0.05$, $\eta_p^2 = 0.20$) demonstrated that lifeguard participants were more accurate at detecting the drowning swimmer than non-lifeguards (77.2% vs. 64.8%, respectively). The main effect of set size ($F(2,96) = 50.0$, $MSe = 166.1$, $p < 0.001$, $\eta_p^2 = 0.51$) was subjected to planned repeated contrasts which noted that the low set size differed from the medium set size ($F(1,48) = 4.2$, $MSe = 295.4$, $p < 0.05$, $\eta_p^2 = 0.08$), and the medium set size differed from the high set size ($F(1,48) = 83.0$, $MSe = 358.4$, $p < 0.001$, $\eta_p^2 = 0.63$) (75.8% vs. 80.8% vs. 56.4% for the low, medium and high set sizes respectively).

Although the interaction between set size and experience group did not reach significance ($F(2,96) = 2.3$, $MSe = 166.1$, $p = 0.103$, $\eta_p^2 = 0.05$), planned repeated contrasts suggested a significant interaction between the low and medium set sizes ($F(1,48) = 4.2$, $MSe = 295.8$, $p < 0.05$, $\eta_p^2 = 0.08$). Figure 18 appears to show that this is driven by the non-lifeguards having a problem detecting drownings in the low set size condition. Figure 19 shows a similar effect over the individual clips, with lifeguards detecting more drownings than non-lifeguards in the low and medium set size, but performance becoming comparable in the high set size.

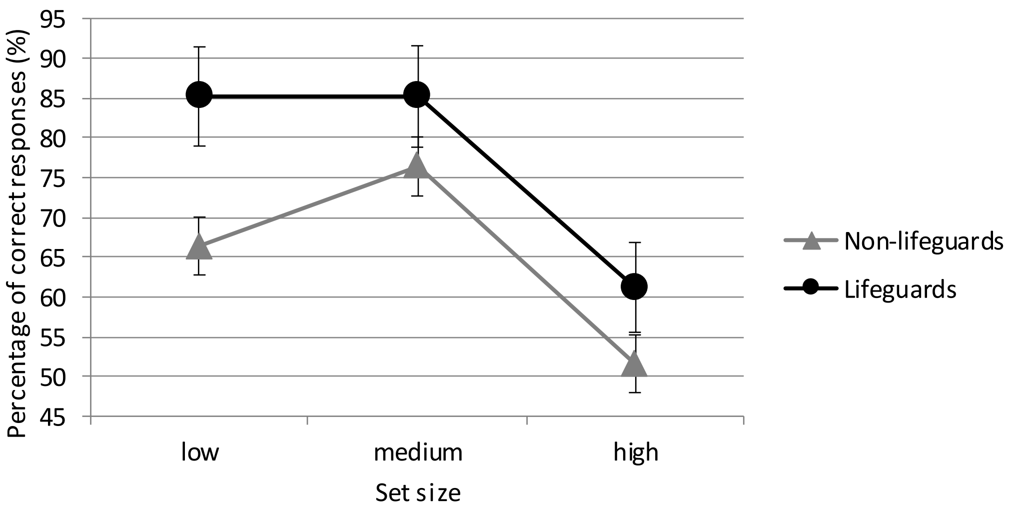


Figure 18. Mean percentage of correctly identified targets (with standard error bars)

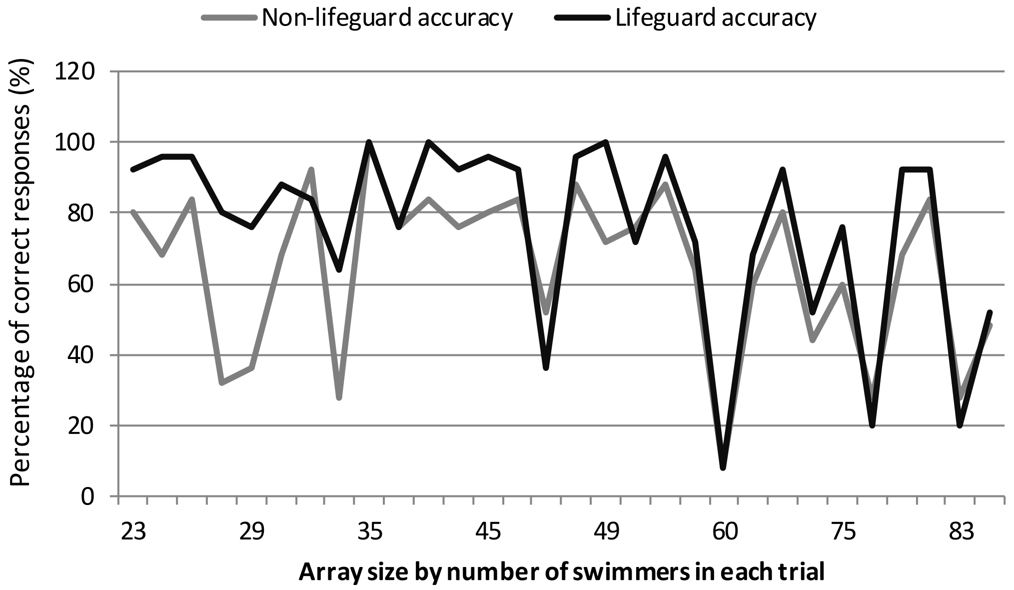


Figure 19. The spread of scores across the individual trials

A similar group x set size (2 x 3) mixed ANOVA was conducted for the response times. Missing data for one participant was noted and this participant was removed from the following analysis. The main effect of experience ($F(1,47) = 8.6$, $MSe = 449285$, $p < 0.05$, $\eta_p^2 = 0.15$) revealed that lifeguards were faster to respond to correctly identified drownings than non-lifeguards (3551 ms vs. 4113 ms, respectively).

The main effect of set size ($F(2,94) = 22.3$, $MSe = 737263$, $p < 0.001$, $\eta_p^2 = 0.32$) when subjected to planned repeated contrasts noted that the medium set-size differed from the high set size ($F(1,47) = 57.7$, $MSe = 1006757$, $p < 0.001$, $\eta_p^2 = 0.55$), but the low set size did not differ from the medium set size ($F(1, 47) = 1.13$, $MSe = 17464567$, $p = 0.29$, $\eta_p^2 = 0.02$) (low: 3603 ms, medium: 3402 ms, high: 4490 ms) (see Figure 20). The interaction between set size and group was not found to be significant.

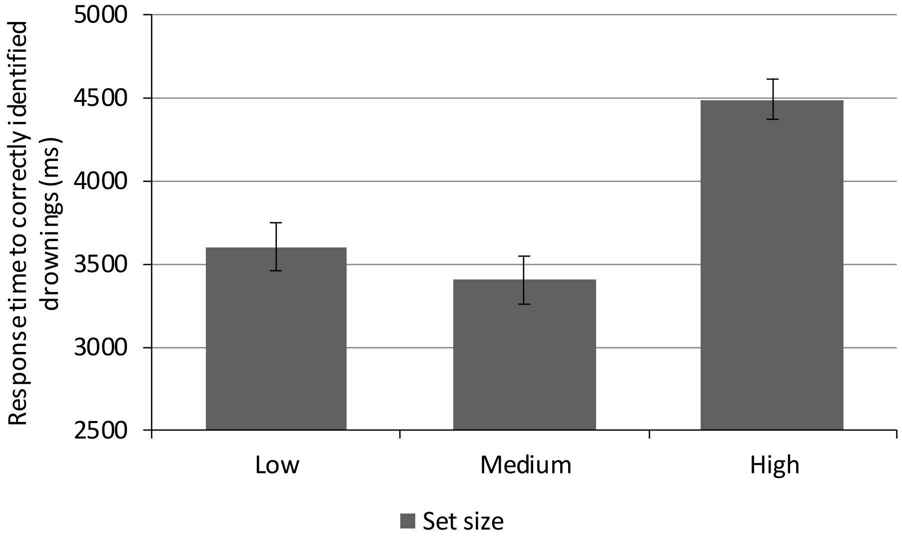


Figure 20. Mean response time to correctly identified drowning targets in ms (with standard error bars)

4.5 Discussion

The results of this first experiment have confirmed the superiority of lifeguard responses to videos of real drowning and distress incidents. Overall lifeguards were able to detect more of the drowning swimmers than the non-lifeguards. These results are similar to the responses seen in Laxton and Crundall (2018), where lifeguards demonstrated superior responses to simulated drownings compared to non-lifeguards. These results of the current experiment support the idea that lifeguard experience influences search skills in more complex trials of real-world environments. Additionally, this experience effect is also in line with other types of surveillance-based visual search tasks in real-world settings, where individuals with more domain experience are noted to have better search outcomes compared to novices in both static and dynamic settings (Curran et al., 2009; Biggs & Mitoff, 2014: Howard et al., 2010).

However, it is interesting to note that absolute performance deteriorates in the highest set size. Both participant groups see a drop of around 20% in detection accuracy in the higher set size from the intermediate set size. For the lifeguard group this suggests that they are only detecting a little over half of the drowning targets, although it appears that they do retain their advantage over the non-lifeguards despite this deterioration in performance in the highest set size.

Why might participant responses be deteriorating in the highest set size? One possibility could be that once the search array becomes too cluttered (e.g. with people, rubber rings), any search advantages that the lifeguards hold in detection are mitigated, as the scene becomes too busy. Once the number of items in the scene grows beyond a certain amount, it is possible that the search zone becomes too difficult to process adequately. If this was the case, more lifeguards would be needed to break cluttered zones into smaller areas of supervision. Similar effects of differing array sizes in dynamic search were reported in a laboratory study conducted by Kunar & Watson (2011). They found that searches for undefined targets (moving letters on a screen) deteriorated search performance in higher set sizes (32 items) compared to searches with fewer items (16 items). These higher set size searches were reported to have more search misses compared to searches with lower array sizes (with undefined targets). While swimmers in a pool differ greatly from moving letters on a screen, both studies have shown the negative impact a high set size can have in an already complex setting, particularly when target templates are relatively unknown (letters of the alphabet or drowning type).

Interestingly, the main effect of set size revealed that medium drownings were responded to more accurately than both the low and high set size, however, when exploring the means of the non-significant interaction effect this appears to be a trend in the non-lifeguard responses, which shows an apparent improvement in medium set size from a relatively poor performance in the low set size. The lifeguard responses remained the same over the low and medium set size, and then trailed off in the high set size. Response times also appear to be negatively affected by set size, with drownings in the high set size being responded to the slowest. While previous research has shown search performance deteriorates as set size increases (Kunar & Watson, 2011), and in the current research the real drowning clips in the larger set sizes has had an adverse impact on performance, it may be possible that the improved responses in the intermediate set size are a result of a change in search strategy between the set sizes. However more research is needed to explore this result, possibly exploring eye movements in these highly complex dynamic stimuli to explore why non-lifeguards are detecting fewer drownings in the lower set size compared to the medium set size and to explore any differences between lifeguard and non-lifeguards' eye-movement over the different set sizes.

Lifeguards were faster to respond to drownings than non-lifeguards. This supports the superiority of lifeguard accuracy to drowning targets found in this experiment. The ability to detect targets earlier may result in more efficient search strategies, such as faster eye-movements, however the eye-tracking results from Experiment 1 would suggest that in simulated drownings there are few differences in lifeguard and non-lifeguard scanning strategies. It may be possible that the faster responses are due to an ability to recognise the characteristics of a drowning swimmer faster than an individual who has not had any formal training in what drowning looks like.

Although the lifeguards detected drownings approximately a second faster than non-lifeguards, it is important to note that, when compared to traditional laboratory visual-search tasks, these response times are relatively slow. Responses in the current experiment were in excess of 3000ms for both groups; however, in the visual-search literature it is common to find participants responding to visual targets only a few hundred milliseconds after onset (Krause et al., 2017; Rich et al., 2008). This highlights the complex nature of these real scenes and shows the difficulty in transferring the results of laboratory studies back to the real world.

This experiment has demonstrated experiential superiority of the lifeguard participants, a result that is similar to the superiority effect found in Experiment 2 (Chapter 3). The effect size for lifeguard superiority in the accuracy of response was also similar between the current experiment and Experiment 2 (η_p^2 = 0.20 vs. 0.22 respectively). This suggests that the superiority of the lifeguards' responses to small numbers of stooge swimmers and simulated drownings can be generalised to large numbers of swimmers and naturalistic incidents and that lifeguard responses to the simulated drownings were not biased by a favourable setting.

One additional result to note is that the lifeguards were just as likely to make false alarm responses on catch trials as the non-lifeguard participants. Previous research has found that lifeguards are less likely to make a response in non-drowning trials (Laxton & Crundall, 2018); however, these were in relatively low set sizes with simulated drownings. It may be that these real drowning clips of highly cluttered swimming pools encourage a lower threshold for responding, resulting in more false positive responses. In real lifeguarding situations a lifeguard needs to make a quick decision to perform a rescue, assessing the situation to engage in an appropriate action or decide how best to proceed (White, 2017). To aid with this decision process lifeguards are encouraged to use colloquial phrases such as ‘when in doubt, check it out’, or ‘if you don’t know, then go’. As a result, it may be that lifeguards are more likely to make false alarm responses in the real drowning clips as the background swimming activity and the drowning behaviours overlap more, than those in the regimented lap swimming of Laxton and Crundall (2018).

Experiment 3 verified that the lifeguard experience effect, previously shown by Laxton and Crundall (2018) and Experiments 1 using artificial stimuli, is evident when using real drowning scenes. However, it provides little information on the processes underlying this effect. To examine this further Experiment 4 measured eye movements of lifeguards and non-lifeguards when watching these real drowning clips.

4.6 Experiment 4

Experience effects in professional searchers have been well documented (Biggs et al., 2013; Howard et al., 2013). This extends into searches of swimming pools, with differences between lifeguard and non-lifeguards noted in previous research (Page et al., 2011; Laxton & Crundall, 2018). However, these were in simulated drowning scenes (Page et al., 2011) with low numbers of swimmers in the pool (Laxton & Crundall, 2017, Experiments 1 & 2). Some results of these studies may be affected by these factors, for instance, in Experiment 1, no differences were noted between lifeguard and non-lifeguard eye-movements post-onset of drowning events. It may be possible that when searches of pools are designed to reflect real life surveillance of busy swimming pools, experience effects in eye movements become apparent, with lifeguards using their experience to guide search to drowning swimmers faster than non-lifeguards.

Previous research into real world dynamic search tasks have found clear differences between experts and novices in eye-movements when carrying out surveillance tasks related to their domain expertise. For example, Bertram et al., (2013) found that expert radiologists used saccades of shorter amplitude when detecting lymph nodes compared to a student control group. Furthermore, Konstantopoulos, Chapman and Crundall, (2010) found experienced drivers were quicker to fixate hazards and fixated safety-relevant stimuli for shorter amounts of time. Experiment 4 therefore aimed to explore any experience differences in the eye-movements of lifeguard and non-lifeguards to the naturalistic clips used in Experiment 3. It is expected that lifeguards will remain superior in their behavioural responses to trials and this superiority will also be found in the eye-movement data, with the lifeguards fixating more of the drowning swimmers and fixating them earlier than non-lifeguards, in line with other real-world experience-based eye-movements.

4.7 Method

4.7.1 Participants

Sixty-two participants were recruited to take part in this second eye-tracking visual search study (with a mean age of 21.7, 34 female). Thirty-one of these participants (mean age 22.8, 7 females) had completed compulsory qualifications in lifeguarding prior to testing and had a varying amount of experience in poolside lifeguard duties (2.5 years of lifeguarding experience on average). Two participants had completed compulsory lifeguarding qualifications, but were noted to be working their first lifeguard shift on the day of testing. The remaining thirty-one participants (mean age 20.4, 27 females) had no lifeguarding experience. Lifeguards were recruited from advertisements on social media sites Linkedin, Twitter and Facebook, and were all from local pools in Nottinghamshire and Leicestershire. Non-lifeguard participants were an opportunistic sample from Nottingham Trent University social science department, made up from a majority of undergraduate students.

4.7.2 Design

A 2 x 3 mixed design was employed, comparing experience group (lifeguards to non-lifeguard participants) to set size of the search array (a low, medium and high number of swimmers). There were 30 drowning present trials that contained active targets. Active targets were classed as swimmers who were displaying the *instinctive drowning response* or distress behaviours of drowning (Pia, 1974; Doyle & Webber 2016). In addition to the 30 drowning-present trials, 15 non-drowning trials were also included. Of the 30 drowning-present trials, ten trials contained low amounts of swimmers (averaging 29.4), ten trials contained medium amounts of swimmers (averaging 46.8), and the remaining ten trials contained high amounts of swimmers (averaging 73.2).

During presentation to participants, all trials were randomised within a single block. All participants viewed all trials. Accuracy and response times to detect the drowning target were recorded. Participants were able to make multiple responses. Incorrect responses were recorded if no response was made in a drowning trial or if a premature response was made that was not followed by a later correct response. It was not possible to respond too late to the drowning, as the clip ended abruptly following the drowning event. Participant's eye movements in each trial were also recorded.

Participants were required to make a push button response if they identified a drowning swimmer. An area-of-interest (AOIs) was placed around the target, which automatically calculated when participants looked at it. AOIs were only active following drowning onset and were invisible to participants. AOIs moved with the drowning target if required, and averaged 2.5cm x 1.8cm in size.

4.7.3 Apparatus and Stimuli

The stimuli were the same as those used in experiment 3.

The experiment was presented on a Dell computer screen connected to an SMI RED500 eye tracker sampling at 500Hz. The trials ran in Experiment Centre as a randomised block. Before each new clip a fixation cross was shown, this would start the next trial when a participant fixated upon it for 500ms.

4.7.4 Procedure

In order to recruit lifeguards, the experimenter arranged testing sessions at various pools and leisure centres around the U.K., with a quiet office or side-room acting as the laboratory. Non-lifeguard participants were tested under similar conditions, using a small room within the university. Participants were given written instructions and asked to fill in a consent form and demographic questionnaire. Prior to the experiment, participants were made aware that they would be searching for any potentially drowning victims from a lifeguard's perspective. Participants were made aware that each drowning trial only contained one drowning incident; however, they could make multiple responses if they thought they had made a false-alarm response. Unlike Experiment 3, participants did not touch the screen to register a response (using the eye tracker precluded this). Instead, participants were told to respond via the zero key on the number pad of a standard keyboard. Once all instructions had been given, participants were given the opportunity to complete a practice trial, which was followed by a final opportunity to ask any remaining questions before the trials began. Participants were given the opportunity to complete a practice trial. Once this was complete, eye tracking calibration took place, which required them to follow a moving cursor with their eyes while sat at 60 cm distance from the screen. Once the participant had been successfully calibrated to the eye tracker the test began. Upon finishing the test, the participants were fully debriefed and thanked for their time and participation. This research was conducted with approval obtained from Nottingham Trent University ethics committee and run in accordance with British Psychological Society guidelines.

4.8 Results

4.8.1 Behavioural data

4.8.1.1 Catch trial responses

The response rates to the non-drowning trials were assessed first. On average, non-lifeguard participants incorrectly responded to 13.1% of catch trials, while lifeguards made incorrect responses to 21.7% of catch trials. This difference was not significant ($t(60) = -1.87$, $p < 0.067$).

4.8.1.2 Signal detection analysis

Measures of *d'* and *c* were calculated for each participant. First, an independent t-test revealed that there was no difference in the *d'* scores between the lifeguards and the non-lifeguards ($t(60) = -.14$, $p = 0.167$), although the lifeguards sensitivity score was 1.62 and the non-lifeguards 1.36, suggesting there was no difference between participants likelihood to detect the target. There was also no difference in the criterion scores ($t(60) = -0.23$, $p = 0.820$), with lifeguards *c* at -1.07 and the non-lifeguards at -1.03, suggesting there is no difference between participants' likelihood to say 'yes' to the signal. .

4.8.1.3 Behavioural responses to drowning present trials

The percentage of trials with a drowning target that received correct responses were analysed next. Trials with a drowning target were considered incorrectly responded to if no response was made following the onset of drowning activity, or participants made a premature response before drowning onset that was not followed by a response in the drowning window. The trials that received correct responses were converted into percentages and subjected to a group x set size (2 x 3) mixed ANOVA. One outlier, who responded to 80% of catch trials, was identified in the lifeguard group. The analysis was run with and without this participant, but the pattern of results was noted to remain the same, thus the following analysis is for 31 non-lifeguards and 30 lifeguards.

A main effect for experience group ($F(1,59) = 19.8$, $MSe = 239.0$, $p < 0.001$, $\eta_p^2 = 0.25$), with lifeguards successfully identifying 75.9% compared to the non-lifeguards identifying 58.3% of drowning targets. When the main effect of set size ($F(2,118) = 47.9$, $MSe = 152.5$, $p < 0.001$, $\eta_p^2 = 0.45$) was subjected to planned repeated contrasts it was noted that the low set size did not differ from the medium set size ($F(1,59) = 0.31$, $MSe = 192.1$ $p = 0.58$, $\eta_p^2 = 0.01$). However, the medium set size did differ from the high set size ($F(1,59) = 64.3$, $MSe = 357.5$, $p < 0.001$, $\eta_p^2 = 0.52$), with more drowning targets being identified in the medium set size compared to the high set size (low: 72.9%, medium: 73.8%, high: 54.6%).

An interaction was noted between experience group and set size ($F(2,118) = 4.2$, $MSe = 152.5$, $p < 0.05$, $\eta_p^2 = 0.07$). The repeated contrasts noted the interaction to be driven by responses in the medium set size being different from the responses in the high set size ($F(1,59) = 5.0$, $MSe = 357.5$, $p < 0.05$, $\eta_p^2 = 0.08$). From Figure 21 it appears that non-lifeguards detected fewer of the drowning targets in the high set size than the medium set size, and this deterioration was greater than the lifeguards drop in accuracy between the medium and high set size.

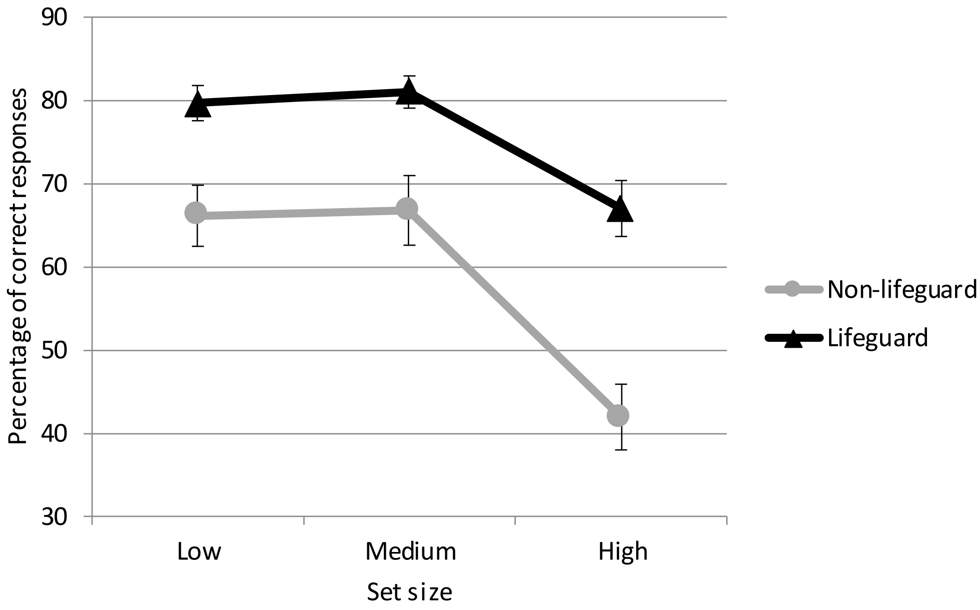


Figure 21. The mean percentages of trials containing a drowning target that were accurately responded to (with standard error bars)

The response times to correctly-identified drowning targets were then subjected to a similar 2 x 3 ANOVA (experience x set size). Three empty cells, where two non-lifeguards and one lifeguard did not make any responses, were noted and these participants were removed from the following analysis. A main effect was found for experience experience ($F(1,57) = 5.9$, $MSe = 1387834$, $P < 0.05$, $\eta_p^2 = 0.09$), which noted that lifeguards' responses within the drowning windows were faster than non-lifeguards (3869 ms vs. 4615 ms respectively).

The main effect of set size ($F(2,114) = 7.4$, $MSe = 1206982$, $p < 0.05$, $\eta_p^2 = 0.11$) was subjected to planned repeated contrasts. This showed that the low set size differed from the medium set size ($F(1,57) = 12.1$, $MSe = 2309870$, $p < 0.05$, $\eta_p^2 = 0.18$), with targets in the low set size being responded to faster than the medium set size. However, there was no difference between the medium and high set size($F(1,57) = 0.02$, $MSe = 2225904$, $p = 0.8$, $\eta_p^2 = 0.00$) (low: 3794 ms, medium:

4481 ms, high: 4450 ms). The interaction between experience and set size was not found to be significant.

4.8.2 Eye movement data

Before analysing the eye tracking data, the tracking ratio for each participant was assessed. All participants had a good tracking ratio average for all trials; therefore, the following analysis is for the same 31 non-lifeguards and 30 lifeguards.

The results for the number of targets that were fixated were analysed first. These were converted into percentages and subjected to an experience group x set size (2 x 3) mixed ANOVA.

The main effect of experience group was not significant ($F(1,59) = 3.3$, $MSe = 196.0$, $p = 0.07$, $\eta_p^2 = 0.05$), although lifeguards fixated 79.6% of targets and non-lifeguards fixated 85.8% of targets. However, the main effect of set size was significant ($F(2,118) = 13.3$, $MSe = 96.0$, $p < 0.001$, $\eta_p^2 = 0.18$). Planned repeated contrasts revealed that this effect was driven by the difference between the medium and high set sizes ($F(1,59) = 11.8$, $MSe= 321.8$, $p < 0.05$, $\eta_p^2 = 0.17$), with targets in the medium set size receiving more fixations than in the higher set size (84.5% vs. 76.7% respectively). The low set size was not significantly different from the medium set size. The interaction between experience and set size did not reach significance.

The time (ms) to make the first fixation to the target from the onset of drowning was subjected to a similar 2 x 3 ANOVA (experience group x set size). The main effect of experience group did not reach levels of significance ($F(1,59) = 0.04$, $MSe = 471062$, $p = 0.8$, $\eta_p^2 = 0.001$) (lifeguards 2135 ms vs. non lifeguards 2171 ms), however the main effect of set size did reach significance ($F(2,118) = 6.4$, $MSe = 846830$, $p < 0.05$, $\eta_p^2 = 0.10$). Planned repeated contrasts revealed there to be a difference between the low and medium set sizes ($F(1,59) = 6.5$, $MSe = 1588763$, $p < 0.05$, $\eta_p^2 = 0.10$), and a difference between the medium and high set size ($F(1,59) = 13.6$, $MSe = 1432554$, $p < 0.001$, $\eta_p^2 = 0.19$) (low: 2239 ms, medium: 1828 ms, high: 2394 ms; see Figure 22). The interaction between experience and set size was not significant.

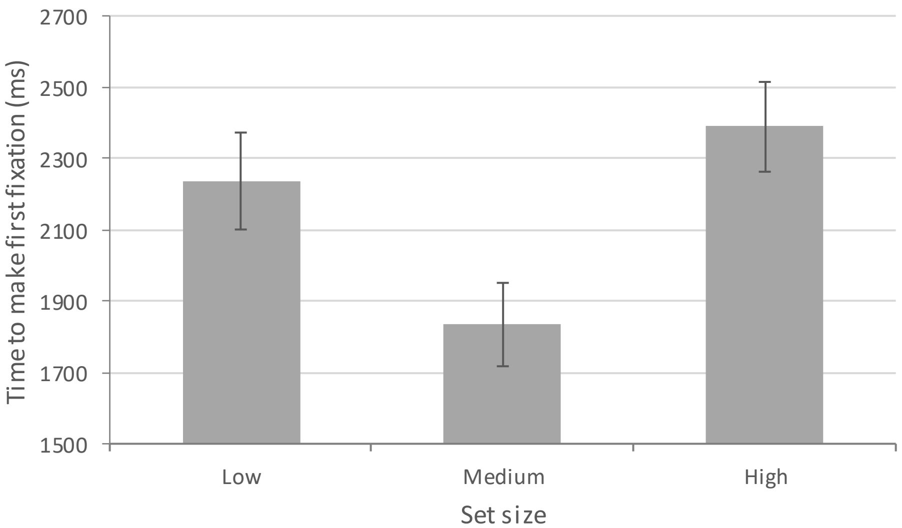


Figure 22. The average time to make first fixation to targets in milliseconds (with standard error bars)

Dwell times as a percentage of AOIs were also subjected to a 2 x 3 ANOVA (experience x set size). A main effect for set size was also noted ($F(2,118) = 99.5$, $MSe = 10.7$, $p < 0.001$, $\eta_p^2 = 0.63$), with repeated contrasts showing that there is a significant difference between the low and medium set size (F(1,59) = 60.8, MSe = 19.2, p < 0.001, η_p^2 = 0.51). There was also a difference between the intermediate and the largest set sizes (F(1,59) = 40.9, MSe = 23.6, p < 0.001, η_p^2 = 0.41), which noted shorter dwell-time percentages of the AOI's in the larger set size (with means of 20.8% vs. 16.4% vs. 12.4%, low, medium and high respectively). The main effect of experience group did not reach significance (F(1,59) = 0.79, MSe = 27.9, p = 0.37, η_p^2 = 0.01)(lifeguards – 15.8% vs. non-lifeguards - 17.1%). The interaction between the experience group and set size did not reach significance.

The number of fixations made to drowning swimmers following onset were also analysed using an experience group x set size (2 x 3) mixed ANOVA. The main effect of set size (F(2,118) = 42.3, MSe = 2.2, p < 0.001 η_p^2 = 0.42) was subjected to planned repeated contrasts. This reveal that the low set size differed from the medium set size (F(1,59) = 23.2, MSe = 4.4, p < 0.001, η_p^2 = 0.28), and the medium set size differed from the high set size (F(1,59) = 18.8, MSe = 4.3, p < 0.001, partial eta = 0.24) (low: 8.0, medium: 6.7, high: 5.6).

The main effect for experience group (F(1,59) = 0.13, MSe = 8.13, p = 0.718, η_p^2 = 0.00) (lifeguards – 6.8 vs non-lifeguards – 6.7) and the interaction between experience group and set size (F(1,118) = 0.07, MSe = 2.15, p = 0.927, η_p^2 = 0.00) were not significant.

4.8.2.1 Processing speeds

Further analysis was conducted, looking at the time between first fixations and response times. The time between the first fixation to the target and a behavioural response was calculated to assess processing time. Responses where a target was not fixated were not included in the analysis. This was then subjected to a group x set size (2 x 3) mixed ANOVA.

The main effect of experience was not found to be significant ($F(1,59) = 2.97$, $MSe = 2279051$, $p < 0.09$, $\eta p2 = 0.48$), although the lifeguards had a processing time of 1913 ms and the non-lifeguards had a slightly slower processing time of 2580 ms. The main effect of set size ($F(2,118) = 6.24$, $MSe = 5511904$, $p < 0.05$, $\eta p2 = 0.10$) when subjected to planned repeated contrasts revealed that the low set size differed to the medium set size ($F(1,59) = 16.14$, $MSe = 3660661$, $p < 0.001$, $\eta p2 = 022$), but the medium set size did not differ from the high set size ($F(1,59) = 0.80$, $MSe = 6011949$, $p = 0.37$, $\eta p2 = 0.01$) (low: 1684, medium: 2668, set size 9: 2387). The interaction between experience and set size did not reach levels of significance.

4.9 Discussion

The results of Experiment 4 have confirmed the predicted superiority of lifeguard responses to real drowning and distress, with more complex scenes, and are in line with those of Experiment 3. Lifeguards correctly identified more drowning and distressed swimmers than the non-lifeguards. This superiority was also reflected in the response times to drowning and distressed swimmers, with lifeguards making responses that were over 500ms faster than non-lifeguards.

It should be noted that the non-monotonic set-size effect that has been noted in the previous experiments presented in this thesis was not present in the current experiment. Although there was an interaction between set size and experience in the accuracy of drowning detection in Experiment 4, this appears when the number of swimmers increases from the medium set size to the high set size, with responses being negatively affected. This differs from previous research that has found detection of drowning over different set sizes to follow a non-monotonic effect, with detection being most influenced at the intermediate set size (Laxton & Crundall, 2018). The set-size results of the current experiment are more in line with previous research in real-world type searches that has found performance in a task decreases as set size increase (Wolfe, Alaoui-Soce & Schill, 2017; Wu & Wolfe, 2016).

Interestingly, the eye movement data showed no signs of a different search strategy being employed between lifeguards and non-lifeguards. This is evident in the failure to find a difference between the two participant groups in the current experiment. In other real-world visual search tasks it is demonstrated that having experience in a certain domain shapes the outcome of search, with experts being faster to fixate targets, making shorter fixations, and also making fewer re-visitations than novices or people with no experience at all (Konstantopoulos, Chapman & Crundall, 2010; Borowsky & Oron-Gilad, 2013; Howard et al., 2010). However, the results of this experiment have followed a similar pattern to those in Experiment 1, which also failed to find a difference between lifeguards and non-lifeguards. Similar results were seen in Page et al., (2011), who also found no difference in eye-movement data was between experienced lifeguards and novice lifeguards. In both the current study and in Page et al., experienced lifeguards were able to detect the drowning swimmer more often than those with less experience, which suggests that lifeguards' superior performance is not necessarily reflected in their search strategy. This raises the possibility that other skills or benefits from training are responsible for lifeguard superiority in these tasks. The higher rates of detection in the lifeguards may be due to other contributing cognitive mechanisms, such as a better ability to track multiple objects (following swimmers around a pool), or to split their attention to different areas of the pool (Functional Field of View).

The complex real-life stimuli used in the experiment and the difficult task of lifeguarding may offer some understanding of the lack of difference in the number of fixations made to the drowning swimmer when comparing lifeguards and non-lifeguards. Typically in visual search tasks, observers make fewer re-visitations to the array items, and individuals with experience in a search domain are often believed to make fewer re-visitations than individuals with less experience (Drew, Boettcher & Wolfe, 2017; Charness et al., 2001). In these real drowning and distress situations, the target drowning behaviour is a developing event. A swimmer may be fine one moment, but in the next few seconds they may become distressed or begin to show signs of the *instinctive drowning response*. It may be that due to these developing situations the lifeguard needs to make multiple glances to a particular swimmer to assess whether their risk of a drowning incident had increased. These re-fixations allow monitoring of other swimmers in-between fixations on the target-to-be. Conversely, if the lifeguard fixates a particular swimmer for too long without looking away, an incident in a different area of the lifeguard's zone may occur and subsequently be missed. Therefore, making multiple re-visitations to items in the pool would be beneficial for the lifeguard in preventing potential critical events.

The eye movement data across the set size condition was in line with previous findings, which suggest that as set size increases and performance on the task decreases (Kunar & Watson, 2011). The greatest decrease in performance appears to be between the medium set size and the high set size. This is apparent on all eye-tracking measures except the time to make first fixation. This drop in performance at the high set size may be a negative influence of the screen array becoming too cluttered. With lots of swimmers in the pool, all moving around, and more overlap between drowning behaviours and the fun play of background swimmers. The array becomes too hard to systematically scan as the pool becomes busier, with observers potentially having to become reliant on salient features drawing their attention or having to very quickly recognise the characteristics of a swimmer in distress as they move their eyes around the search area.

A central issue is the ambiguous response time window, which may have reduced the effect size for the lifeguard superiority. There are also potential issues with post-perceptual decision-making biases, which will be discussed more in the following section. A third experiment using these real drowning clips was therefore undertaken to further explore the superiority effect of lifeguard participants. This experiment employed an occlusion technique in which the video is stopped and overlaid by a still frame which is blurred out to prevent further extraction of detail from the scene. This was done to test if information can be extracted from the scene within a couple of seconds following drowning onset and if drownings can still be accurately located, without the criterion for a response to be made within a given window

4.10 Experiment 5

Experiments 3 and 4 have shown an effect of superiority in lifeguard visual search of real drowning incidents. However, these two studies focussed on post-onset detection of drowning events, giving participants a response window that was open for a varied amount of time, anywhere from 2-19 seconds. In cases where the drowning window is quite long, it is likely that even the non-lifeguards will eventually spot the drowning target. This may reduce the effect size of lifeguard superiority in regard to the number of drowning targets detected and be affecting the sensitivity difference between lifeguards and non-lifeguards in the real-drowning clip experiments.

One alternative to relying on potentially confounded response times is to use an occlusion task, which measure some elements of hazard prediction (Crundall, 2016). Prediction tasks employing an occlusion factor have recently been explored in driving research and have been found to be robust tests for discriminating between novices and experts (Lim, Sheppard & Crundall 2014; Castro et al., 2014; Ventsislavova et al., 2019). Occlusion tasks in visual search are believed to isolate the predictive element in domain specialist search, as the occlusion factor allows for accuracy of responses to be measured, without being confounded by a criterion bias of responses times (Pradhan & Crundall, 2017).

An example of this comes from research conducted by Crundall (2016), who found that a hazard prediction driving task consistently discriminated between experienced and novice drivers, with the prediction task being a more robust measure of response accuracy, as response time tasks may be influenced by underlying factors such as processing times, confirmation of hazards or hazard appraisals. It was suggested that the occlusion task employed in hazard prediction removes such factors and allows for the researcher to focus on the predictive factors of driving hazard perception. Similar findings were seen in Crundall and Eyre-Jackson (2015), who report that expert police officers were better than control participants at identifying the type of crime that is about to be committed in an occluded CCTV footage. These results also suggested that the police participants were more sensitive to the imminent possibility of a crime being committed in the occluded CCTV footage. Using the occlusion method to distinguish between expert and novice in these dynamic settings shows that certain professional domains can use information from the scene to guide eyes to the appropriate area at an appropriate time.

If drowning detection were to be explored using a similar occlusion task it may be possible that experienced lifeguards' superiority may be even more apparent as they are forced to rely more upon prediction of drowning events based on antecedent behaviours. Additionally, an occlusion task might be better able to capture the sensitivity of the lifeguards by focusing upon detection in the early seconds of drowning onset.

To investigate an element of prediction for drowning events in occluded response windows, Experiment 5 aimed to explore drowning detection with the use of an occlusion point in each clip. Median response times from Experiment 3 were used to create an occlusion point in the real drowning videos used in that experiment. It is expected that this altered methodology will elicit a greater difference between lifeguards and non-lifeguards, with the non-lifeguard participants detecting fewer drownings than lifeguards in this experiment. The accuracy of responses over the set sizes should also follow an expected pattern, with a decrease in accuracy as set size increases.

4.11 Method

4.11.1 Participants

Fifty participants were recruited to take part in the third visual search experiment using real drowning incident videos (mean age 23.2, 29 female). Twenty-five of these participants (mean age 24.3, 9 female) had completed compulsory qualifications in lifeguarding prior to testing and had a varying amount of experience in poolside lifeguard duties (4.24 years of lifeguarding experience on average). The remaining twenty-five participants (mean age 22.0, 20 females) had no lifeguarding experience. Lifeguards were recruited from local leisure centres and recreational parks in the East Midlands. Non-lifeguard participants were an opportunistic sample mainly from a university population.

4.11.2 Design

The same design was used as Experiment 3, comparing experience group (lifeguard vs. non-lifeguard) to set size (low vs. medium vs. high), in a 2 x 3 design, with the exception of an occlusion screen appearing partway through the incident.

The median response times of the first 15 lifeguards and 15 non-lifeguards from Experiment 3 were used to create cut-off points for an occlusion task. The time frames for the occlusion screen can be seen in Table 5. At the median response point a blurred occlusion frame was presented, with participants required to either touch the location on the screen where they detected a distressed swimmer, or touch a black box in the right-hand, bottom corner of the screen to indicate no drowning had been seen.

Accuracy of responses was recorded, with a responsive window placed around the target area (measuring 250 x 140 pixels in the horizontal and vertical axes respectively). The response window accounted for 0.8% of the total screen area. Correct responses were noted if a drowning swimmer was correctly identified, or if the trial was correctly identified as a no drowning trial. If a response was given outside of the responsive window then an incorrect response was noted.

4.11.3 Apparatus and Stimuli

The video clips used in Experiment 5 were the same as those used in Experiment 3, however the median response times of the first 15 lifeguard and 15 non-lifeguard responses were used as a cut-off point in which an occlusion screen was shown (details can be seen in Table 5 in Chapter 2). The no-drowning response box was placed in the right bottom corner (as seen in Figure 23). No swimmers were occluded by the 'no drowning' response box, with the box covering either the end of the pool or a section of pool that had been roped off.

Like Experiment 3, a Lenovo Yoga touch screen laptop was used, with a screen resolution of 2880x1620, running Psychopy. The trials were run in a randomised block, with a feedback screen after each trial. Participants were able to make localised response on the touch screen of the laptop.

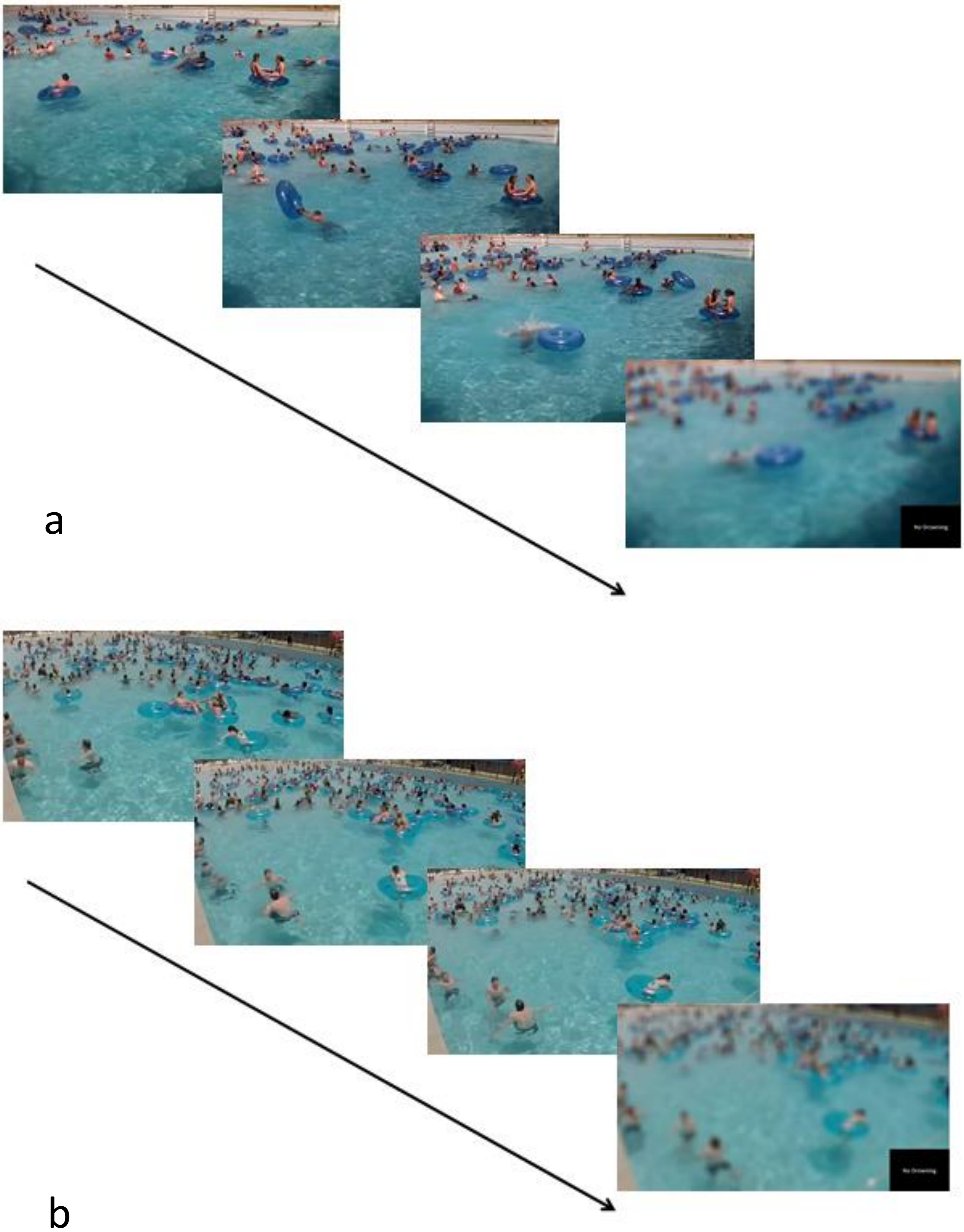


Figure 23. A timeline of screen shots from the a) low set size and b) high set size occlusion experiment, from the start of the trail, to the onset of drowning, to the last frame before occlusion, and the occlusion screen with the no drowning response box in the bottom-right corner.

4.11.4 Procedure

The procedure was the same as that used in Experiment 3.

4.12 Results

4.12.1 Behavioural data

4.12.1.1 Catch trial responses

The response rates to non-drowning trials were assessed first within the behavioural responses. On average non-lifeguard participants made an incorrect response to 28.8% of trials, while the lifeguard participants made an incorrect response to 25.9% of trials. There was no difference in the number of trials incorrectly reponsed to between the non-lifeguards and lifeguards ($t(48) = -0.58$, $p = 0.57$).

4.12.1.2 Signal detection analysis

Measures of *d'* and *c* were calculated for each participant. First, the difference was noted in the measure of *d'* between lifeguards and non-lifeguards ($t(48) = -2.67$, $p < 0.05$), with average scores of 1.09 and 0.47 respectively, suggesting that lifeugards were more likely to detect the target. No difference was noted between the criterion scores of lifeguards and non-lifeguards ($t(48) = -0.56$, $p = 0.581$), with average scores of -0.52 and -0.60 respectively, suggesting there is no difference between participants' likelihood to say 'yes' to the signal.

4.12.1.3 Behavioural responses

Correct responses to drowning-present trials were then assessed. Trials with a drowning target were considered incorrectly responded to if a response was made to an incorrect location, or a 'no drowning' response was made. The trials that received a correct response were then converted into percentages and subjected to a group x set size (2 x 3) mixed ANOVA. There were no outliers in the data; therefore, the following analysis is for the whole data set.

A main effect of experience group ($F(1,48) = 17.7$, $MSe = 256.6$, $p < 0.001$, $\eta_p^2 = 0.43$) revealed that lifeguards were more successful in correctly identifying the drowning swimmer than non-lifeguards (63.5% vs. 44.4% respectively). The main effect of set size ($F(2,96) = 33.4$, $MSe = 198.1$, $p < 0.001$, $\eta_p^2 = 0.41$) when subjected to planned repeated contrasts demonstrated that there was no difference between the low and medium responses ($F(1,48) = 1.4$, $MSe = 401.5$, $p = 0.2$, $\eta_p^2 = 0.03$), but the medium set size differed from the high ($F(1,46) = 31.8$, $MSe = 510.2$, $p < 0.001$, $\eta_p^2 = 0.40$) (low: 61.4%, Medium: 58.0%, high: 40.1%).

The interaction between experience and set size fell just outside of conventional levels of significance ($F(2,96) = 2.9$, $MSe = 198.1$, $p = 0.058$, $\eta_p^2 = 0.06$). However, planned repeated contrasts revealed a significant difference between the medium and high set sizes (F1,48) = 4.5, $MSe = 510.2$, $p < 0.05$, $\eta_p^2 = 0.09$). Figure 24 appears to show that this is driven by the decreased accuracy of lifeguard responses when faced with a high number of swimmers.

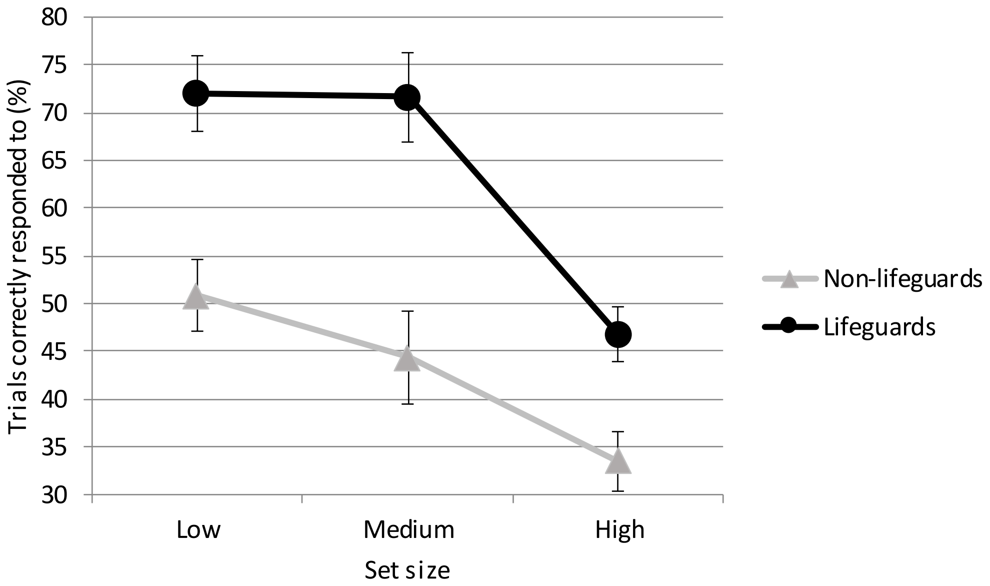


Figure 24. Mean percentage of correctly identified targets (with standard error bars)

A similar group x set size (2 x 3) mixed ANOVA was conducted for the percentage of no-drowning responses recorded during drowning present trials. A main effect of group ($F(1,48) = 5.4$, $MSe = 183.2$, $p < 0.05$, $\eta_p^2 = 0.10$) revealed that lifeguard participants made fewer no-drowning responses compared to non-lifegard participants (24.9% vs. 33.2 respectively). The main effect of set size ($F(2,96) = 13.3$, $MSe = 171.2$, $p < 0.001$, $\eta_p^2 = 0.22$) when subjected to planned repeated contrasts reveal the low set size differed to the medium set size ($F(1,48) = 9.8$, $MSe = 327.3$, $p < 0.05$, $\eta_p^2 = 0.17$), but the medium did not differ from the high set size ($F(1,48) = 3.0$, $MSe = 483.8$, $p = 0.089$, $\eta_p^2 = 0.06$) (low: 22.0%, medium: 30.0%, high: 35.2%).

When the interaction between group and set size ($F(2,96) = 9.02$, $MSe = 171.2$, $p < 0.001$, $\eta_p^2 = 0.16$) was subjected to planned repeated contrasts a difference between the medium and high set size was revealed ($F(1,48) = 11.6$, $MSe= 483.8$, p < 0.05, η_p^2 = 0.20), but there was no difference between the low and medium set sizes (F(1,48) = 0.88, MSe = 327.3, p = 0.35, η_p^2 = 0.02). Figure 25 shows this appears to be driven by the lifeguards increased 'no drowning' responses in the high set size. Post hoc Bonferroni adjusted t-tests support this interpretation with lifeguards making fewer no-drowning responses than non-lifeguards in the low and medium set sizes (low: t(48) = 2.9, p < 0.016, & medium: t(48) = 3.3, p < 0.016). However there was no difference between the lifeguard and control responses in the high set size (t(48) = -0.75, p = 0.46), supporting the lifeguards' increase in no-drowning responses in that set size.

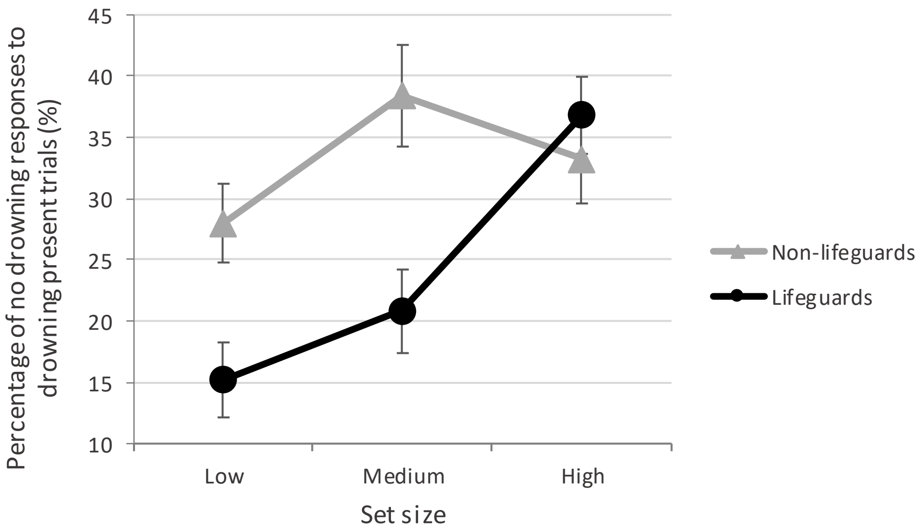


Figure 25. Average percentage of no drowning responses to drowning present trials

Some responses were incorrect since the participant identified a drowning incident on a drowning trial, but an incorrect location was identified. These incorrect responses were also converted into a percentage and subjected to a group x set size (2 x 3) mixed ANOVA. The main effect of group (F(1,48) = 7.04, MSe = 173.3, p < 0.05, η_p^2 = 0.14) revealed that lifeguards made fewer false alarm responses than non-lifeguards (12.3% vs. 22.4% respectively). The main effect of set size ($F(2,96) = 17.03$, $MSe = 117.7$, $p < 0.001$, $\eta_p^2 = 0.27$) when subjected to planned repeated contrasts revealed that the low set size differed from the medium ($F(1,48) = 5.0$, $MSe = 213$, $p < 0.05$, $\eta_p^2 = 0.09$) and the medium set size differed from the high ($F(1,48) = 28.4$, $MSe = 280.0$, $p < 0.001$, $\eta_p^2 = 0.37$) (low: 16.2%, medium: 11.6%, high: 24.2%). The interaction between group and set size failed to reach significance.

4.13 Comparison between Experiments 3 and 5

The similar design between Experiment 3 (fast-as-possible localised touch screen responses) and Experiment 5 (localised responses after occlusion) meant that the accuracy of responses could be compared. This analysis will determine which type of test brings out a greater effect in lifeguard superiority.

A 2 x 2 x 3 (experiment x experience group x set size) mixed ANOVA was carried out on the percentage of drowning swimmers identified, either by touch location after occlusion, or a localised, fast-as-possible touch screen response.

The main effect of experiment ($F(1,98) = 35.19$, $Mse = 206.9$, $p < 0.001$, $\eta_p^2 = 0.27$) revealed that more drownings were detected in Experiment 3 than in Experiment 5 (71.0% vs. 54.1%). The main effect of experience group ($F(1,96) = 29.9$, $MSe = 206.9$, $p < 0.001$, $\eta_p^2 = 0.22$) noted that lifeguards detected more drownings than non-lifeguards (70.3% vs. 54.6% respectively).

The main effect of set size ($F(2,192) = 79.3$, $MSe = 182.1$, $p < 0.001$, $\eta_p^2 = 0.45$) when subjected to planned repeated contrasts revealed that the low set size did not differ to the intermediate set size (F(1,96) = 0.2, MSe = 348.7, p = 0.7, η_p^2 = 0.00), however the intermediate set size differed to the high set size (F(1,96) = 103.4, MSe = 434.5, $p < 0.001$, η_p^2 = 0.52) (69.0% vs. 69.8% vs. 48.6%, respectively). None of the interactions reached conventional levels of significance.

Although a three-way interaction between experiment x group x set size approached significance (F(2,192) = 2.7, MSe = 182.1, p= 0.072, η_p^2 =0.03), it should be noted that planned repeated contrasts revealed a significant interaction between the low and intermediate set size (F(1,96) = 4.6, MSe = 348.7, $p < 0.05$, η_p^2 = 0.05). It appears from Figure 26 that this is driven by the improved responses of the non-lifeguards in the intermediate set size of Experiment 3.

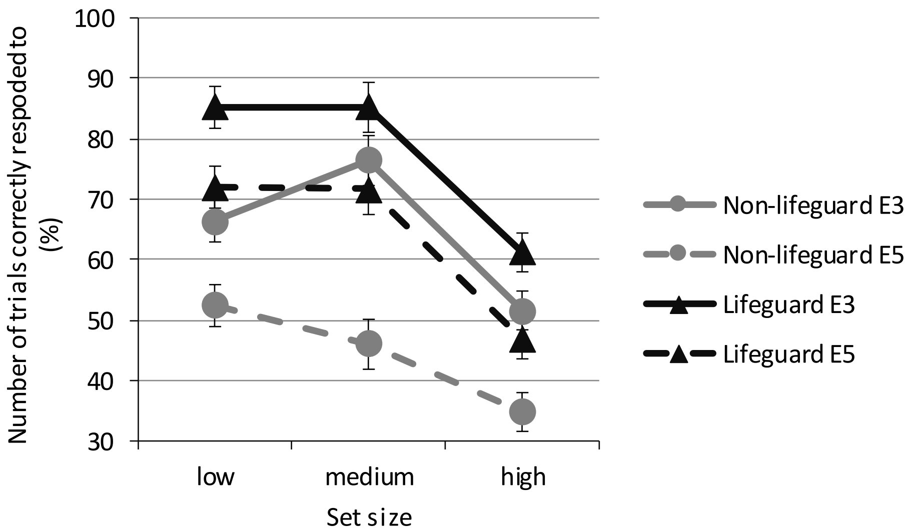


Figure 26. Average of correct responses as a percentage across experiments 1 and 3 (with standard error bars)

4.14 Discussion

The results of Experiment 5 have followed a similar pattern of results to Experiments 3 and 4. Lifeguard participants in Experiment 5 were found to have superior responses to drowning present trials compared to non-lifeguard participants. The superior performance of lifeguards is also in line with the findings of Laxton and Crundall (2018) and Experiments 1 and 2 (Chapter 3) where lifeguards detected more simulated drowning swimmers than non-lifeguards during searches of dynamic (but staged) pool scenes. In conjunction with the results from Experiments 3 and 4, this consistent experience effect demonstrates that lifeguard drowning detection performance in the real drowning trials translates from the simulated and highly controlled task in Laxton and Crundall (2018) and the Experiments of Chapter 3.

One potentially important finding to note is the difference between the methodologies of Experiments 3 and 5. The exploration into the two studies has demonstrated that the occlusion method employed in Experiment 5 produced a larger effect size for the difference between lifeguards and non-lifeguards than the response time study employed in Experiment 3. This greater difference is potentially due to focusing the task in Experiment 5 on more subtle cues and removing the ability to respond once the target becomes unambiguously drowning. For example, in Experiment 3 some longer clips may have elicited more responses than the shorter clips, meaning those who may not have initially seen the hazard or drowning in the early stages are getting a chance to respond at a later point, potentially altering the accuracy effect size between the two groups. During searches of longer clips, participants would have more time to look through the search display after drowning onset rather than relying on early cues, which would fail to show the benefits of experience in the accuracy of responses. The greater effect for the occlusion task (partial eta 0.43 compared to 0.20 of Experiment 3) is in line with other research, which has demonstrated that occlusion tasks are a more robust way of assessing accuracy of responses as the ambiguous response time windows are removed (Pradhan & Crundall, 2017).

The superiority of lifeguard responses in the occlusion trials used in Experiment 5 demonstrates that lifeguard participants are able to detect drowning signals early in critical incidents. Additionally, these results may potentially demonstrate that lifeguards may use pre-onset information and cues when detecting drowning events, bringing in an element of prediction. Similar responses have been noted in hazard prediction research using similar occlusion-based tasks to discriminate between experienced and novice drivers (Ventsislavova at al., 2018; Crundall, 2016). For example, Crundall (2016) reported that discrete precursors to hazards provided better discrimination between experienced and novice drivers, with occlusion screens happening early in the hazard.

In the current experiment, lifeguard participants were found to make fewer incorrect 'no drowning' responses during drowning present trials (incorrect rejections) and fewer incorrect responses to drowning present trials, where a non-drowning swimmer was incorrectly identified as the drowning target. This was particularly apparent in the low and medium set size for 'no drowning' responses during drowning present trials. This demonstrates that the lifeguards are able to better recognise and respond to drowning signals compared to non-lifeguards, though extremely high set sizes may still pose a problem.

Responses in the low and medium set size received a similar number of correct responses from lifeguards, however in the high set size accuracy of responses declined. This decline was greater in this experiment than in the first experiment, with responses in the high set size dropping to below 50% for both lifeguards and non-lifeguards. These results demonstrate how much harder the occlusion task is compared to the response time task. This shows that the changed methodology is reducing the cues available (making the task harder overall) but also increasing the effect size between groups.

These results also demonstrate the difficult nature of visual search in real-world conditions, particularly when the search area becomes extremely crowded. It is likely that crowding degrades the subtlest of cues first, making the occlusion task much harder in the high set size. Lanagan-Leitzel et al., (2015) have reported a negative effect of crowing on a lifeguards' search of a swimming pool, with response times to drowning and emergency situations becoming delayed as the physical space between swimmers becomes visually cluttered. In terms of the decreased accuracy results in Experiment 5, it may be a reflection of a degraded ability to successfully monitor swimmers in a pool that is becoming highly busy with visual cues becoming downgraded. It may be that when the pool reaches a certain capacity additional lifeguards could be provided to break pool numbers into smaller zones and allow for all visual information in the zone to be processed, including the detection of any drowning swimmers.

The improved performance in the drowning present trials in the medium set size compared to the low set size that was found in Experiment 3 has not been replicated in Experiment 5. A similar effect with responses to active drowning being responded to better at an intermediate set size compared to a low set size was also noted in Laxton and Crundall (2018). One possible explanation for Experiment 5 not following a similar pattern to previous research exploring drowning detection in naturalistic scenes may be a result of the different methodological approach. It may be that using an occlusion task relies on participants being able to detect and process the drowning swimmer earlier, eliminating the longer time period that participants would have to scan the area. The removal of the non-monotonic effect is another success for the occlusion methodology, suggesting that the possible effect found in earlier experiments was due to some odd post-detection processes that has now been removed.

4.15 General Discussion

All three experiments in this chapter (Experiments 3, 4 and 5) have consistently shown lifeguards to have superior detection of drowning swimmers in a naturalistic search task, with higher rates of accurate responses from lifeguards compared to non-lifeguards, although this was not always noticeable in the top-level comparisons of *d'* across groups. Experiments 3 and 4 also demonstrated that lifeguards have faster responses to drowning swimmers. This fits with previous literature exploring effects of experience in dynamic visual search (Howard et al., 2010; Howard et al. 2013). The superiority of lifeguard search found in all three experiments also fits with previous research conducted into lifeguard visual search exploring drowning detection in simulated, naturalistic drowning scenes (Laxton and Crundall, 2018). However, no differences were found between eye-movement measures for lifeguards and non-lifeguards, suggesting that the greater performance of lifeguards may instead result from differences in underlying cognitive mechanisms, rather than a superior visual search strategy per se. One difference between Chapters 3 and 4 is the more complex stimuli used to explore lifeguard drowning detection in Experiments 3, 4 and 5. It could be argued that the pool footage used in experiments in Chapter 3, and in Laxton and Crundall (2018), make for an easier visual search, was highly controlled stimuli, which includes simulated drownings and regimented lap swimming. However, the findings of the studies in Chapter 4 (Experiments 3, 4 and 5) would suggest that lifeguards remain superior in detecting drowning events, even when the search display is highly complex, as with the footage of the real pool environment and drownings. As the simulated drownings in Chapter 3 have elicited similar responses to the real drowning trials in Chapter 4, it may be that in future research actors could be used to simulate drownings in pool environments to create more realistic stimuli, which also benefits from experimental control when exploring lifeguard visual search.

The non-monotonic set size effect that has appeared in Experiment 3, and that also appeared in the active drowning responses of Experiments 1 and 2 in Chapter 3, as well as in previous literature (Laxton & Crundall, 2018) was not found consistently in the experiments of this chapter. In fact, the effect was only found in Experiment 3, and appears to be driven by non-lifeguard responses. This highlights the complex nature of using naturalistic, dynamic stimuli of real-world events. It may be possible that this non-monotonic set size effect was a result of some external or internal influences. For example, the level of stimulation from search stimuli may affect drowning detection when there are low and high numbers of swimmers, Griffiths (2002) suggests that when the search of a swimming pool becomes monotonous, such as only having a few people in the pool, the lifeguards attention and search performance is affected by boredom and task performance is decreased. However, Griffiths also suggested that high levels of arousal, such as busy fun sessions with lots of features also results in poor search performance from lifeguards. The high levels of stimulation with busy pools can easily lead to observers becoming stressed with more objects in the search zone to scan and monitor. Accordingly, for lifeguards in Experiments 3, performance with low and medium numbers of swimmers in the pool potentially provides enough stimulation for the lifeguards to remain focused on the task, but when the number of swimmers increases to a high number of swimmers, the lifeguards may be come overstimulated and search performance suffers. In contrast, non-lifeguards may be under stimulated when there are only a low number of swimmers in the pool, and as the task is not related to their everyday work non-lifeguards may be more likely to lose focus in the lower set size as they become bored with the task. Whereas, when there are a medium number of swimmers in the pool, performance rejuvenates. Although this may be one explanation for the non-monotonic set size effects seen in the first experiment, ultimately it is difficult to understand what might be driving such an effect in some experiments but not in others and highlights the complex nature of naturalistic and dynamic stimuli, and that these searches operate differently from laboratory controlled searches and static searches.

Although the current set of experiments have shown a consistent effect of lifeguard superiority in both accuracy of responses and in the time to respond to drowning events, one limitation of the research presented in this chapter is that it is unclear what may be driving the difference between lifeguard and non-lifeguards' drowning detection skills. If eye-movement data had shown significant differences between the two groups overall, it may have been possible to conclude that differences in search strategy are driving the superior detection of the lifeguards. It could be possible that some other contributing cognitive skill is driving the differences, such as being able to track more moving objects (following swimmers through the pool) or take in more of the pool in a single glance (FFOV). More research is needed to explore this possibility.

4.16 Conclusions

In summary, this experimental chapter has consistently found a superiority effect for lifeguard drowning detection in the behavioural responses, extending previous findings beyond simulated drowning in relatively small set sizes. However, as in Experiment 1, the results of the eye-tracking study in this chapter did not find a difference between lifeguard and non-lifeguard eye movements overall. This again suggests that lifeguards superior drowning detection compared to non-lifeguards is not a result of a better scanning strategy, but rather some other characteristic of search, such as faster processing of drowning behaviours or a better ability to track swimmers around a pool. In this chapter it was also noted that the occlusion method of testing lifeguard visual search produced a greater differentiation (in terms of effect size) between mean lifeguard and non-lifeguard performance, suggesting that this may be a more robust way of testing lifeguard drowning detection in the future. Going forward, the next chapter will begin to explore cognitive skills that may be contributing to lifeguard visual search.

Chapter 5
An exploration into the contributing cognitive skills of lifeguard visual search

Chapters 3 and 4 examined lifeguard visual search in a naturalistic and dynamic visual search task, in both simulated and real drowning/distress incidents. These 5 studies have consistently shown an experience effect, with lifeguards detecting drowning swimmers faster and more often than non-lifeguards. Therefore, given that the results from previous experiments are consistent with research indicating that experts have better search performance (e.g. Howard et al., 2013; Biggs et al., 2013; Faubert, 2013), and that lifeguards are better at detecting hazardous events (Lanagan-Leitzel & Moore, 2010; Page et al., 2011; Lanagan-Leitzel, 2012), the following experiment will explore contributing cognitive skills that may shape lifeguard visual search. The results of this experiment may help to inform future training tools to improve lifeguard drowning detection.

5.1 Introduction

Although lifeguard experiential effects have been found in previous research (Page et al., 2011; Laxton & Crundall, 2018) and in the first four experiments of this thesis, it is still unclear where this drowning detection superiority comes from.

If we explore the nature of lifeguard surveillance, contributing or underlying cognitive skills may become clear. First, when a lifeguard is looking in the pool environment, it would be an advantage to have a greater sensitivity for detecting drowning characteristics in extra-foveal vision. These could include monitoring swimmers engaging in dangerous behaviours, any swimmers in distress or experiencing drowning, or featural changes such as the clarity of the water. To successfully monitor a swimming pool zone, a lifeguard would need to rapidly respond to any changes in the environment. These changes will often occur in peripheral vision first, with attention needing to be shifted to explore all areas of the pool zone. This kind of swimming pool surveillance has similarities to other areas of real-world research, such as driving (Crundall, 2016; Crundall, Underwood and Chapman, 1999; Mackenzie & Harris, 2015), where greater sensitivity to extra-foveal target features is a typical characteristic of safer drivers.

A second skill that lifeguards may have developed is the ability to track swimmers around the pool, following their trajectories, noting any changes in behaviour and observing when people enter or leave the pool area. Two domain-free cognitive tasks that seem most related to these skills in the role of pool surveillance are the Field of View (FFOV) and Multiple Object Tracking (MOT). These two tasks will be detailed in the literature below.

5.1.1 Introduction to Functional Field of View

The Functional Field of View task describes a very similar construct to the Useful Field of View (UFOV) task, which is a theoretical construct that is used to measure the information extracted within a single glance and a branded test (Ball et al., 1988). Unlike the UFOV, the FFOV is not solely tied to a particular test. The UFOV task was first introduced to assess higher order cognitive abilities, such as speed of visual processing and localization of targets under conditions of divided attention. Both the FFOV and UFOV tasks capture the ability to rapidly detect and identify targets, with visual attention divided between central and peripheral locations (Wood & Owsley, 2014).

In previous versions of UFOV and FFOV tasks, a central stimulus is briefly flashed while the participants hold fixation at the centre of the screen (see Figure 27). The stimuli for the central target are often simple, such as letters or a simple shape (Ball et al., 1988; Motter & Simoni, 2008; Richards, Bennett, Sekuler, 2006).

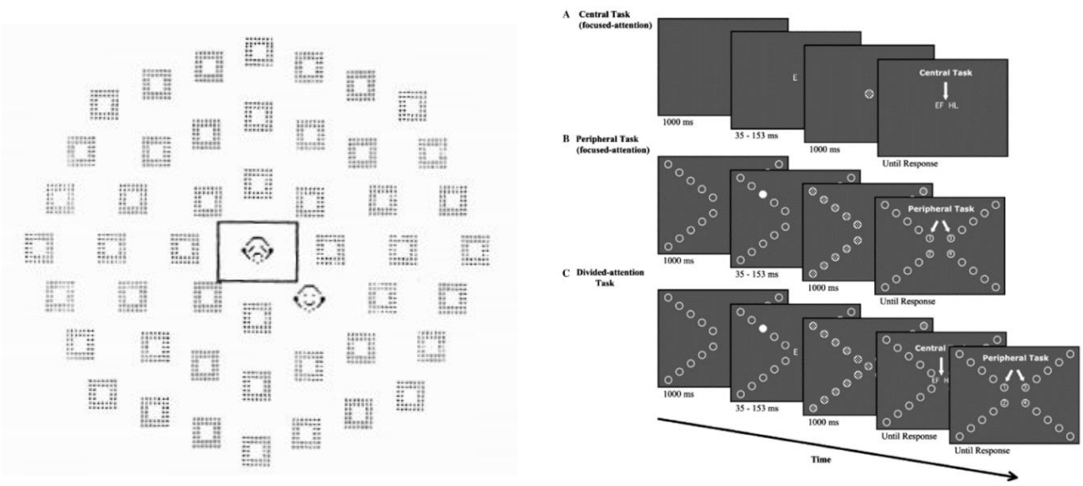


Figure 27. Left: Schematic representation of the type of stimulus used in the UFOV task (Ball et al., 1988); Right: Schematic illustration of the stimuli used in Richards et al. (2006)

Both the UFOV and FFOV capture the ability to rapidly detect and localize targets in extra-foveal regions, even if one is required to process a stimulus at the point of fixation (Wood & Owsley, 2014). Such tasks may be relevant for a lifeguard who needs to be sensitive to changes in any swimmer's status, even though they may not be looking directly at that particular swimmer at the time of change. When both the central target and the peripheral target are presented as a pair, with one stimulus presented in the centre of an individual's view and a second presented in one of eight cardinal locations around the central target, divided attention can be measured. Having to divide attention to more than one location is relevant to a number of real-world events, particularly in searches of dynamic scenes where objects move in and out of the central view of an individual's visual attention, such as driving, sports games, or lifeguarding.

5.1.1.1 UFOV/FFOV and applications to the real world

Many real-world applications can be made with the UFOV and FFOV tasks. While there has been very limited research into the cognitive skills that contribute to lifeguard surveillance, other applied domains have used UFOV and FFOV tests to explore effects of cognitive abilities. There are a number of factors that can affect how much we see and the information we take in from the world around us, including domain experience, age, or cognitive load (Crundall et al., 2002; Coeckelbergh et al., 2004; Williams, 1982). For example, in a recent study by Song et al., (2015) it was noted that children with autism spectrum disorder have a narrower functional field of view compared to typically developing children, with the number of stimuli correctly detected and identified decreasing as the eccentricity from the fovea increased more so in the children with autism spectrum disorder.

In real world applications, there has been extensive research into the effects of UFOV and FFOV in driving (Atchley & Dressel, 2004; Gasper et al., 2016; McManus, Cox, Vance & Stavrinos, 2015; Wood, Chaparro, Lacherez, & Hickson, 2011). For example, McManus et al., (2015) found in a laboratory task that the third sub-test of the UFOV task, which assesses selective attention, significantly predicted motor vehicle collisions in a simulated driving task conducted by young drivers.

5.1.1.2 Factors affecting UFOV/FFOV

Experience in a certain skill can influence how much information is taken in during a single glace. Crundall et al., (1999) suggested that inexperienced drivers utilise different search strategies compared to experienced drivers when driving on the road, which was potentially due to the cognitive demands of driving. In novice drivers, the FFOV is expected to be narrower, as novices need to redirect more attention to the point of fixation in order to process stimuli. For more experienced drivers, the foveated stimuli are less novel and have a lower threshold for identification. As such, experienced drivers do not need to reallocate extra-foveal attention to the point of fixation and are therefore more sensitive to the appearance of peripheral targets.

As expected, Crundall et al., (1999) found that experienced drivers had the best responses to peripheral targets, and inexperienced drivers had the worse. When on-road hazards were present (e.g. a car ahead suddenly displays brake lights), peripheral target detection decreased for both driver groups, though the inexperienced drivers always performed more poorly. This suggests the appearance of a hazard was fixated by drivers, with attentional resources reallocated from extra-foveal regions to the point of fixation in order to process the hazard. In a later study by Crundall, Underwood and Chapman (2002) it was found that the FFOV of experienced drivers did degrade to same absolute level as that of learner drivers (and was therefore a *relatively greater* degradation than that suffered by learner drivers), but this happened in very short bursts. Experienced drivers appeared more able to process the hazard quickly during this burst of intense concentration at the point of fixation, and then rapidly reallocated resources back to the extra-foveal regions. Thus, it appeared that the two groups utilised different strategies for processing hazards, in regard to the time course of deployment of extra-foveal attention. Experienced drivers may have developed a strategy to reduce the time they are inattentive to peripheral locations, leading to less degradation over time.

It has been argued that the difficulty of the current perceptual load determines how much information can be taken in within a single glance. Lavie (1995) explored this through a flanker task using target letters (z or x) in low set size conditions (target appeared alone) and high set size conditions (target appeared with 5 non-target letters). A critical distractor letter was also presented, which was either compatible (a letter Z when the target was a z) or incompatible (a letter X when the target was a z, or vice versa) (see Figure 28). The results demonstrated that there was less distraction from near-by incompatible flankers when there was high perceptual load. However, it was suggested that the incompatible flanker negatively influenced response times to the central letter only in low demand conditions (501 ms vs. 452 ms, for incompatible and compatible respectively), with no effect in the high set size condition (613 ms vs. 594 ms, incompatible and compatible respectively). This is presumably due to the spotlight of attention being narrower in the low set size conditions.

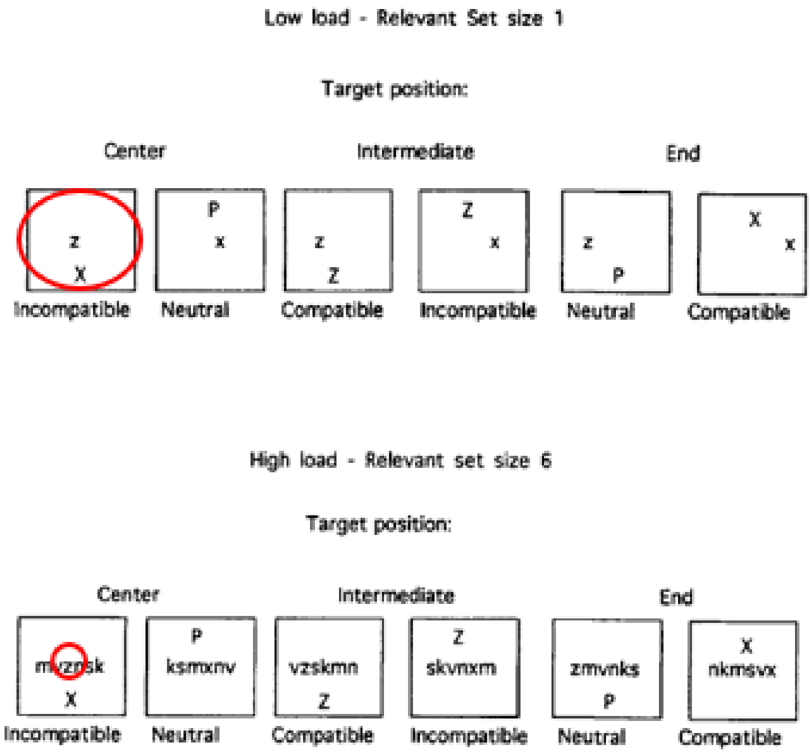


Figure 28. An example of the incompatible flanker task used in Lavie (1995) with the top task showing the low set size condition and the bottom task showing the high set size task. The red circles are added to demonstrate how extrafoveal attention might be deployed. In the relatively easy task on the top row, the FFOV can be set wide (which inadvertently allows the distractor to be processed also. The harder task on the bottom row requires a tighter focus of attention resulting in the distractor falling outside extra-foveal attention.

Even the cognitive demands of a non-visual task can have an impact on the information extracted during a single glance. Atchley and Dressel (2004) explored the effect of conversation whilst driving and found that the Functional Field of

View was vastly restricted in participants engaged in conversation during a laboratory-based cognitive task. In regard to lifeguarding, it may be possible that inexperienced lifeguards have a smaller field of functional view, especially when faced with increasing task demands, such as an increased number of swimmers or greater perceived ambiguity of swimmers' behaviours. This could have a positive benefit in that it may reduce the impact of nearby distractors on identifying drowning characteristics at the point of fixation, but it may also reduce the possibility that lifeguards may spot and reorient to ostensible drowning behaviours in extra-foveal vision.

5.1.2 Introduction to Multiple Object Tracking/Avoidance

As stated earlier in Chapter 1, MOT theory suggests that an individual is able to track a small number of moving objects during visual search by pre-attentively tagging each item, which then allows each tagged item to be followed around the screen (Pylyshyn, 1998). In typical MOT tasks, observers are shown a fixed number of identical objects in a display. A number of these objects are identified as target items, by either being briefly highlighted or by briefly flashing in the display. Then, all the items begin to move, following individual and random trajectories. After a varied tracking period, the items stop moving and the observer must identify whether a probed item falls within the target set. The tracking task provides a measure of sustained attention to the positions of multiple objects because observers must continuously update their representations of objects' positions. Accuracy in MOT is noted to decline as the number of targets increases, which suggests a capacity limit to tracking (Pylyshyn & Storm, 1988).

Theories of MOT have proposed that only a small subset of items can be attended to and subsequently tracked. Pylyshyn and Storm (1988) found that up to five targets in an array of ten can successfully be tracked. However, as the number of items in the search array increased, accuracy of tracked items decreased. MOT has also been argued to better capture attentional aspects of sustained attention to dynamic stimuli (Cavanagh & Alvarez, 2005) and in application to real-world tasks has been found to be associated with better or worse performance in domain-specific tasks (Mackenzie & Harris, 2015; Bowers et al., 2011).

With regard to lifeguarding, MOT may be relevant for tracking swimmers moving around the pool. This could include following a subset of swimmers or monitoring the whole pool, tracking where swimmers are and predicting their trajectories.

5.1.2.1 Multiple object tracking in the real world

While there has been limited research into lifeguard visual search skills and contributing cognitive mechanisms, other areas of real-world search have explored the factors that may influence search skills. For example, Allen et al., (2004) explored the ability to track multiple objects in professional radar operators. This profession requires operators to use radar to monitor, control and supervise aircrafts as they move through the environment. One of the findings suggested that the professional radar operators have flexible strategies that are resistant to attentional demands during simultaneous tasks, with expert radar operator participants tracking more targets than undergraduates on both single and dual task conditions. Furthermore, Vaeyens, Lenoir, Williams and Philippaerts (2017) found that expert football players used a goal oriented search strategy, fixating players in relation to their position with the ball and switching between that player and other areas of the display, this lead to greater search performance in terms of faster decision times and more accuracy of responses. It may be that this greater ability to track things in the environment resulted in the superior expert performance in these tasks.

While MOT tends to be a passive task, with observers using a single fixation point to monitor all items, Wolfe et al., (2007) note that tracking in real-world settings tends to differ, with items frequently moving in and out the observers' visual attention and items in the tracked set changing identify over time. In a study to explore these factors, Wolfe et al., employed a multiple object juggling task, which is similar to a typical MOT task (fixed MOT), but items are added and subtracted from the tracked set and target items are identified after the start of a tracking episode (dynamic MOT). The targets added to the set were briefly highlighted after onset and subtracted targets had a red 'X' placed over the top. The results showed that observers are able to maintain tracking (four items across both fixed MOT and dynamic MOT) with items being added in or subtracted from the tracked set with little impact on tracking rate.

MOT in the real world can also be complicated by the need to remain vigilant to events. Event detection refers to the identification of one of the followed targets as it transitions into a critical target worthy of response. The capacity to track events often appears to be limited in comparison to the tracking capacity of more traditional multiple object tracking; 2-3 events compared to 4 items (Wu & Wolfe, 2016). To explore how multiple events are tracked, Wu et al., (2018) employed a monitoring task that used identical grey circles as the items in the display, moving among static black dots. To differentiate target grey circles from non-target grey circles, each target had one of the black dots attached to them. The target event occurred when one or two of the grey circles 'dropped' the smaller black one (see Figure 29). Two targets events were presented, with events happening at the same time or at different times. The results showed that event monitoring for two different events is successful when there are fewer items in the array (4 vs. 8). However, it was also noted that multiple event monitoring becomes further limited when there are multiple events in one time period, and when there is uncertainty about the event onset, which was affected further if there was a level of uncertainty about the additional events. The results of Wu et al. suggest that simple MOT studies may considerably over-estimate the probability of detecting events that occur while successfully tracking multiple objects.

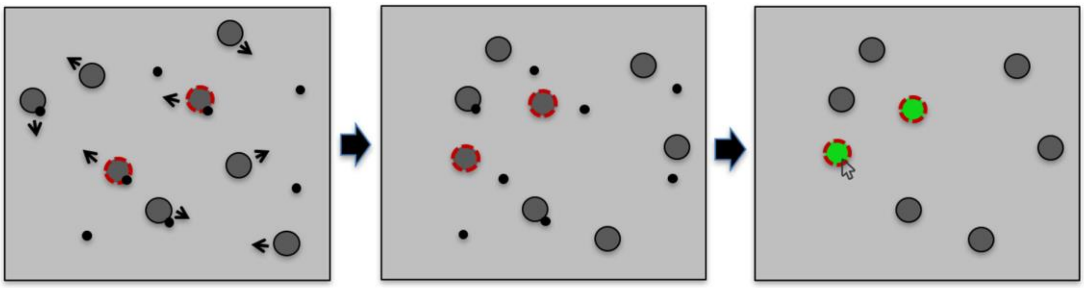


Figure 29. The stimuli and procedure used in Wu et al., (2018). Target grey circles (highlighted in red) are attached to smaller black circles and target events occur when the small black circles are dropped (middle image). The right image shows the participants selection, with selected items in green.

5.1.2.2 Interactive multiple object avoidance

The MOT task is generally passive in nature, with the observer often fixating a central location and covertly tracking a subset of items. This passive observation may not be reflective of real-world tasks, such as driving or lifeguarding, which generally require more active viewing, with more eye and head movements. Often in real world tasks people are required to interact with the environment around them to some degree. For example, a car driver needs to be able to control the car whilst also maintaining visual attention. In lifeguarding there is a changing priority hierarchy, where some swimmers become more important (displaying drowning behaviours) and others less so (those display normal swimming activity) over the duration of a surveillance shift. To account for such task demands recent research has explored more interactive versions of the standard MOT task (Thornton et al., 2014; Mackenzie & Harris, 2017).

The MOT task typically requires observers to track a subset of items that are cued in some way for a few seconds while they move around a screen with identical items. Once the items stop moving, the observer has to identify the cued items from the other identical items. In comparison, these interactive avoidance tasks usually require participants to interact with one or more items on the screen so that they avoid colliding with other items. The number of items that participants can have on-screen at any one time has been noted to be higher than the number of items that are tracked in traditional MOT tasks, however this could be due to participants only needing to track a subset of distractors at any one time (Thornton et al., 2014).

The multiple object avoidance (MOA) task is a recent example exploring cognitive control and visual attention. In the MOA task, one item is controlled while a number of other dynamic objects are avoided. If the controlled object collides with one of the other items, the task will end. More items are added to the display the longer a participant successfully avoids the other items (Mackenzie & Harris, 2017). The MOA task incorporates many eye-movements, as the spaces around the controlled target item need to be explored in order to avoid colliding with any of the moving distractor items. Mackenzie and Harris (2017) suggest that throughout this task continual eye-movements need to be made to successfully avoid a collision. In the same study MOA was found to be a strong predictor of driving ability. While both MOT and MOA are predictors of driving ability, the MOA is potentially more reflective of active, dynamic tasks where shifting subsets of tracked distractors may be monitored and more eye-movements are elicited in successful searches. MOA may therefore be a better test to the underpinning skills of a lifeguard. In a pool environment, the lifeguards are unlikely to use a single fixation point to track swimmers (as might happen in MOT), thus the MOA task may be a more practical domain-free cognitive task to explore tracking skill.

5.2 Experiment 6

Based on the discussion of the literature above, Experiment 6 aimed to explore any differences between trained lifeguards and non-lifeguards' skills in a multiple object avoidance task and a Functional Field of View task. Task scores for these two cognitive tests were compared to performance on a shorted version of the occlusion drowning-detection task that was employed in Experiment 5 (Chapter 4), this was to identify whether the underlying cognitive tasks relate to drowning detection.

The domain-free MOA task aimed to measure how long multiple object avoidance could be maintained, with the task increasing in difficulty as time progresses (one new ball added to the display every 10 seconds). The partially domain-free FFOV tasks aimed to measure the information extracted by lifeguards and non-lifeguard participants from a dynamic central target (displaying either the drowning behaviours or casual fun swimming) and a peripheral target (appearing in one of eight locations).

It is hypothesized that higher performance on the MOA and FFOV will be positively associated with drowning-detection performance in the occlusion task. It is also expected that lifeguard participants will be more successful in both the MOA and FFOV tasks compared to the non-lifeguards, maintaining multiple object avoidance for longer, accurately identifying the central target more often and have a larger field of view, detecting the location of a peripheral target more often.

5.3 Method

5.3.1 Participants

Sixty participants were recruited to take part in a visual search study (with a mean age of 24.33, 31 female). Thirty of these participants (mean age 21.5, 11 females) had completed compulsory qualifications in lifeguarding prior to testing and had a varying amount of experience in poolside lifeguard duties (3.98 years of lifeguarding experience on average). The remaining thirty participants (mean age 27.17, 20 females) had no lifeguarding experience. Lifeguards were recruited from advertisements on social media sites including Linkedin, Twitter and Facebook, and were all from the U.K. Non-lifeguard participants were an opportunistic sample from the U.K.

5.3.2 Design, Stimuli and apparatus

5.3.2.1 Multiple Object Avoidance (MOA) task

Design

A between subject design was employed for the MOA task, which compared experience group (lifeguard vs. non-lifeguard). The task started with three distractor balls, with one new ball was added to the display every 10 seconds. The number of active balls present at the end of a trial (after a collision, see Figure 27) and the time multiple object avoidance was maintained were recorded as the main dependant variables. These measures were averaged across 5 trials.

The trial lasted until the participants were unable to avoid the distractor balls.

Stimuli and apparatus

Each trial started with a blue ball, which was controlled by the curser, which in turn was controlled by the laptop touchpad. The ball could be moved freely around an 800 x 800 screen resolution window. Three red balls were also presented at the beginning of each trial and moved randomly around the screen (see Figure 27). Every 10 seconds a new ball was added to the array until the controlled blue ball collided with one of the red circles. The speed of the moving red balls was randomised across trials, and each individual ball moved at a different speed.

The experiment was created in Psychopy, using Python coding and presented on a Lenovo Yoga touch screen laptop, with a screen resolution 2880 x 1620. This program was provided by Dr. Andrew Mackenzie and is identical to that reported in Mackenzie and Harris (2017).

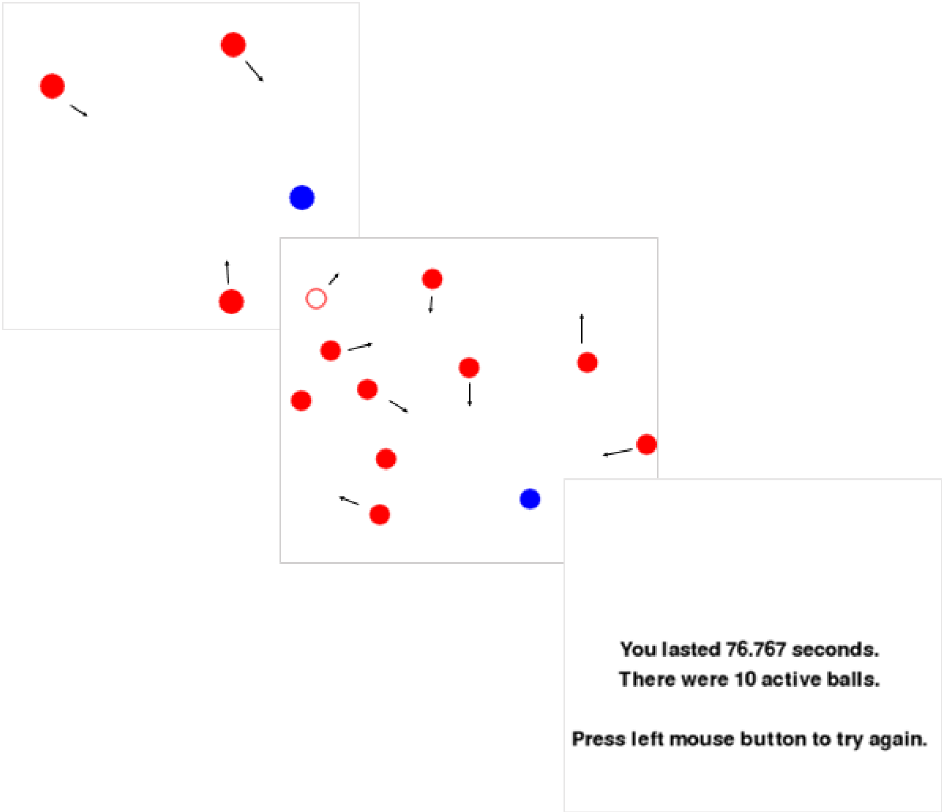


Figure 30. Three screen shots from the MOA task. Top: The test starts with three red balls. The participant must move the blue ball to avoid a collision. Middle: Successful participants have an extra ball added every ten. Here a tenth ball has just been added. It remains transparent for 1000 ms seconds, during which time collision detection is suspended. Bottom: The feedback screen after a collision has occurred.

5.3.2.2 Functional Field of View (FFOV) task

Design

A Functional Field of View task was also employed, using a 2 x 2 mixed design. This compared experience (lifeguard vs. non-lifeguard) to the central task (drowning vs. swimmer) and in a separate analysis experience to the eccentricity of the peripheral target (near vs. far). There were 56 central targets, twenty-eight of which were a drowning swimmer. A further twenty-eight central targets were catch trials that did not involve a drowning swimmer. The peripheral targets were positioned in one of eight locations, four near the central target

(200 pixels from the centre of the screen) and four further away in the shape of a cross (325 pixels from the centre of the screen). The location of the peripheral targets (left, right, above and below the central target) was considered to be a factor as there was no theoretical reason to predict an asymmetry in FFOV as one might expect in other domains such as reading (Jordan et al., 2014; Paterson et al., 2014).

The central swimmer appeared for 3 seconds. During presentation the peripheral target appeared in one of the eight locations for 300 ms and randomly between 0.5 and 2.5 of the central targets' presentation. On the next screen participants were asked to press 1 on the keyboard if they thought the swimmer was drowning or 0 if they were not. They then had to tap the location in which one of the eight peripheral targets appeared, via a localised touch screen response.

Stimuli and apparatus

The stimuli from Experiment 3 were used as the central target. A small area of the swimming pool was presented on a grey background. This was achieved by placing a grey mask with an aperture cut out of it over the top of the full video clip.

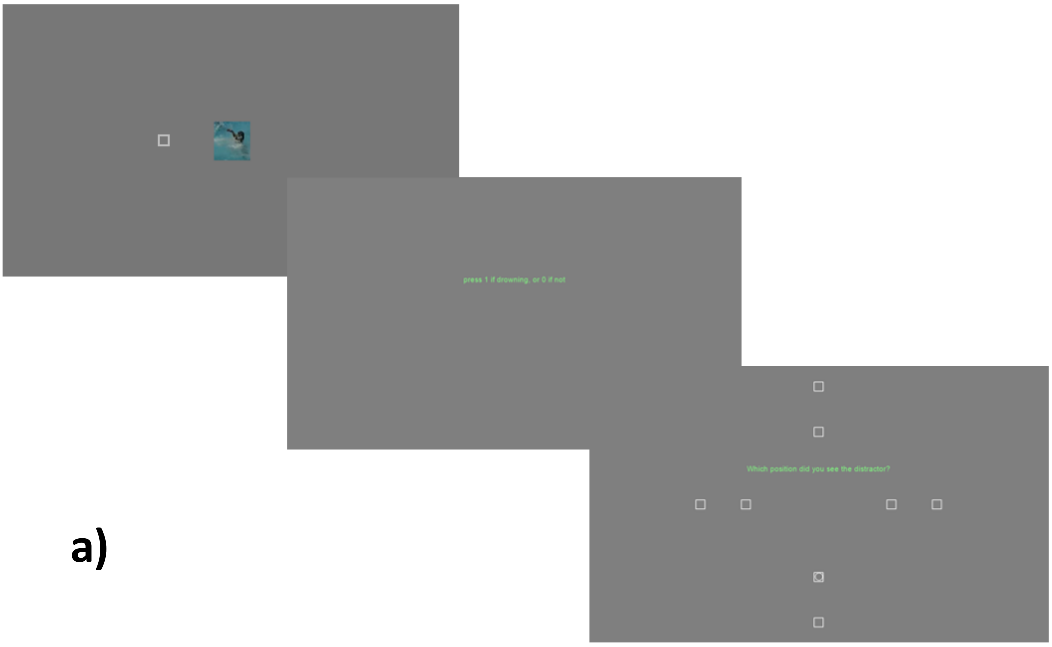
The mask (Psychopy colour 0,0,0) with a 150 pixels x 150 pixels square window in the centre of the screen was placed over the video with one swimmer appearing in the window. Video clips were moved under the mask, so that the target swimmer was within the central window, located on a 1280 x 720 screen resolution. Only one swimmer was presented in the central window. The swimmer appeared for 3 seconds and either displayed drowning and distressed behaviours (e.g. the *Instinctive drowning* response) or fun swimming behaviours (e.g. splashing, handstands, jumping).

During presentation of this central target a 50 x 50 pixel grey outline of a square (pyschopy colour 0.2,0.2,0.2) (see Figure 31) appeared in one of 8 locations, randomly without replacement. This peripheral target had a random stimulus onset asynchrony of 0.5 and 2.5 seconds following the appearance of the central target. The peripheral target appeared for 300 ms. A central fixation cross was displayed before presentation of each trial for 500 ms.

After each trial two further screens were displayed. The first asked participants to respond with a 1 on the keyboard if the central target was drowning and a 0 if not. The second screen asked where the peripheral target was displayed. This response screen had all the potential peripheral locations displayed and required participants to make a touch screen response on a location via a laptop touch screen.

The experiment was created in Psychopy, using Python coding and presented on a Lenovo Yoga touch screen laptop, with a screen resolution 2880x1620.

The study was run with two other short tasks in Experiment 6 (the MOA task and the drowning detection occlusion task), with the order of the three tests being switched between participants to avoid any order effects.


press 1 if drowning, or 0 if not
Which position did you see the distractor?

a)

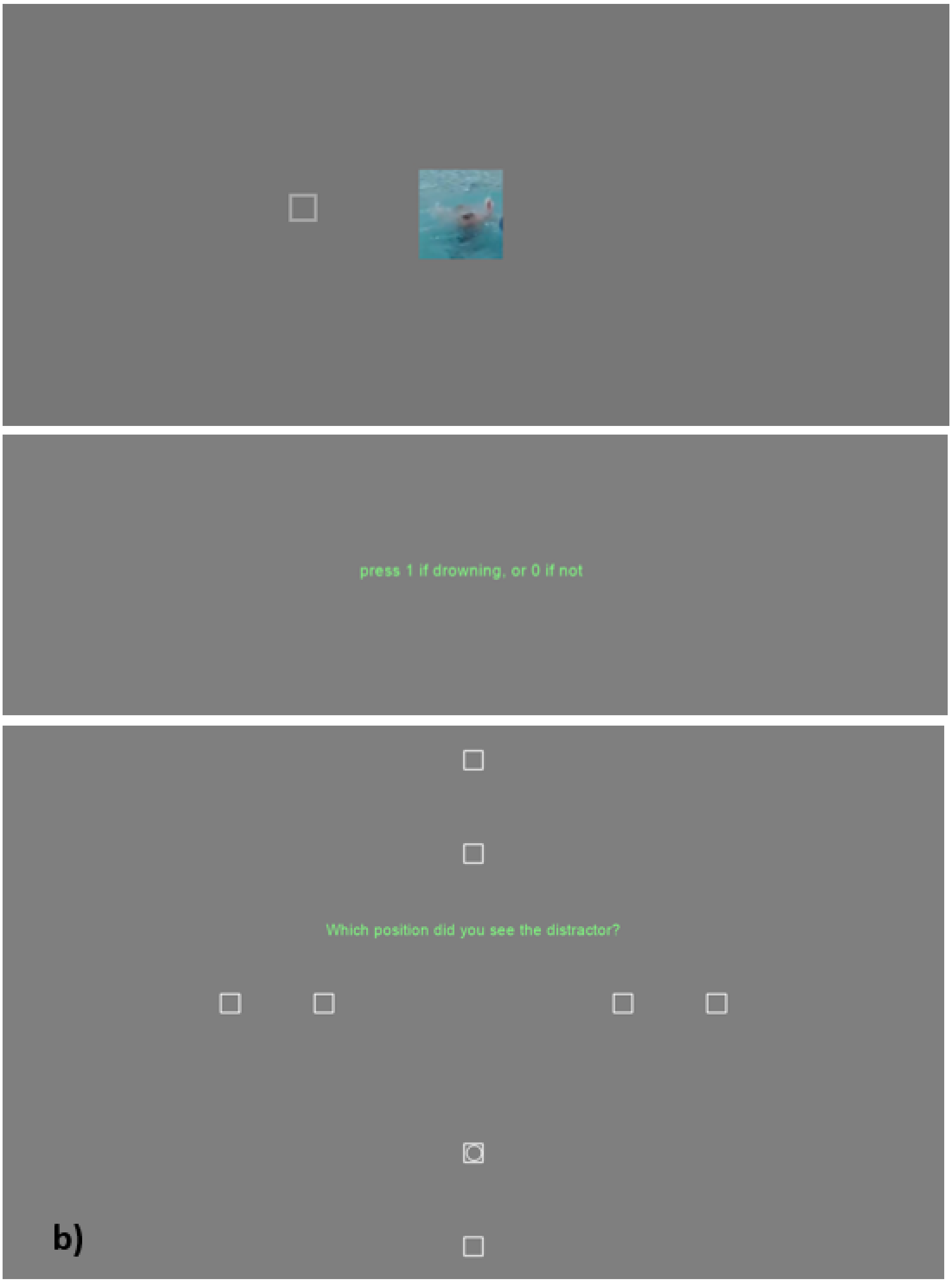


Figure 31. a) Three screen shots taken from the FFOV study stimuli in presentation order. b) Top: first screen with the central target appearing in the window and peripheral target appearing in one of the eight locations. Middle: the response screen for the central target. Bottom: The response screen for the peripheral targets, with all potential locations visible.

5.3.2.3 Occlusion task

Design

Performance on the FFOV and MOA had to be related back to a measure of lifeguard performance. The occlusion task from Experiment 5 was chosen to provide this measure of drowning detection ability. A between-subjects design was employed for the occlusion task, with the independent variable being the level of experience (lifeguards vs. non-lifeguards). The dependant variable was the number of drownings detected.

Ten drowning clips were included in this experiment. These clips were the 10 clips that had the largest difference in accuracy between lifeguard and non-lifeguard responses in Experiments 3 and 5 combined. Three non-drowning clips were chosen at random, one for each set size. The presentation of these 10 clips was the same as in Experiment 5. The 10 drowning clips and 3 non-drowning clips were randomised for all participants within a single block. Non-drowning clips were included to reduce participant guessing.

A shortened version of the occlusion task from Experiment 5 was employed, with the video clip freezing and picture becoming blurred a couple of seconds post-drowning onset. Participants were required to either touch where they detected a distressed swimmer, or touch a black box in the right-hand, bottom corner of the screen to indicate no drowning had been seen. Accuracy of responses was recorded, with a responsive window placed around the target area (measuring 250 x 140 pixels in the horizontal and vertical axes respectively). The response window accounted for 0.8% of the total screen area. Correct responses were noted if a drowning swimmer was correctly identified, or if the trial was correctly identified as a no drowning trial. If a response was given outside of the responsive window, then an incorrect response was noted.

Stimuli and apparatus

The video clips used in the occlusion task were 13 clips from Experiment 5. Ten drowning clips were selected that had the largest difference in accuracy between lifeguard and non-lifeguard responses in Experiments 3 and 5 combined. These clips were Wavepool rescue videos 4, 6, 13, 18, 19, 20, 22, 34, 40, and 42 (see Table 2 in Chapter 2). The three catch trials were chosen at random, one from each set size was selected. These were Wavepool rescue catch videos 1, 2, and 5.

Videos clips played in full, with an occlusion screen presented at the end of the video. The no drowning response box in the occlusion screen was placed in the right bottom corner (see Figure 32).

Video stimuli that were selected for the occlusion task did not also appear as a central target in the FFOV task.

As with Experiment 5, a Lenovo Yoga touch screen laptop was used, with a screen resolution of 2880x1620, running Psychopy. The trials were run in a randomised block, with feedback screen after each trial. Participants were able to make localised responses on the touch screen of the laptop.

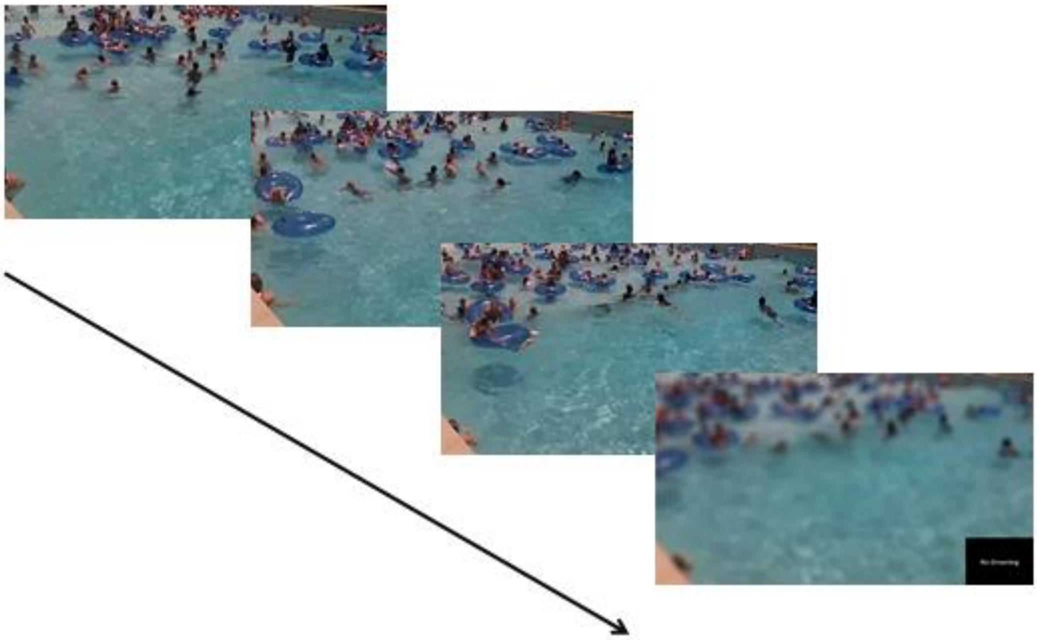


Figure 32. A timeline of screen shots from the start of the trail, to the onset of drowning, to the last frame before occlusion, and the occlusion screen with the no drowning response box in the bottom-right corner.

5.3.3 Procedure

In order to recruit lifeguards, the experimenter arranged testing sessions at various pools and leisure centres around the U.K. with a quiet office or side-room acting as the laboratory. Non-lifeguard participants were tested under similar conditions. Participants were given written instructions and asked to fill in a consent form and demographic questionnaire. Prior to the study the participants were made aware of the nature of the experiment and that they would see short clips that may be distressing, but nothing that a lifeguard may face within their daily surveillance role. Once all instructions had been given, participants were given the opportunity to complete a practice trial for the first task, which was followed by the chance to ask any further questions. When the participant was happy all questions had been answered, the first block of the experiment began. A practice trial was given before each of the three tasks was completed. Upon finishing the three tasks, the participants were fully debriefed and thanked for their time and participation. This research was conducted with approval obtained from Nottingham Trent University ethics committee and run in accordance of British Psychological Society guidelines.

5.4 Results

5.4.1 MOA study

The number of balls that participants managed to accrue on the screen was assessed. On average the maximum number of balls on the screen for non-lifeguard participants was 4.6, while the maximum number of balls achieved by the lifeguard participants was 5.1 balls ($t(58) = -2.92$, $p < 0.05$) (see Figure 33).

The amount of time that participants successfully avoided the balls was then assessed. On average non-lifeguard participants successfully avoided the multiple balls for an average of 21.83 seconds, while the lifeguards successfully avoided the balls for an average of 26.58 seconds ($t(58) = -2.74$, $p < 0.05$) (see Figure 33).

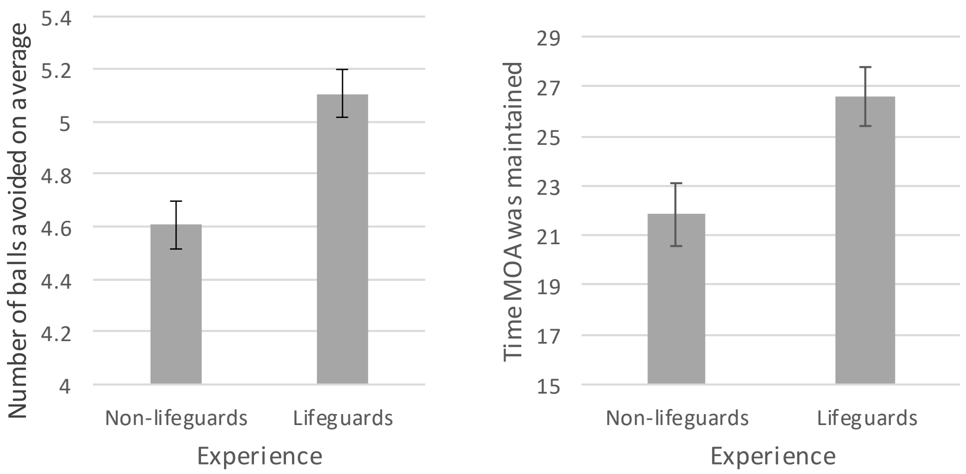


Figure 33. Left: average number of balls successful avoided on average (with standard error bars), Right: Time in seconds that MOA was successfully maintained (with standard error bars)

5.4.2 FFOV Study

The responses to the central target were analysed first for the FFOV data. A response was noted as correct if a drowning target was successfully identified or a non-drowning target correctly rejected. Responses were converted into percentages and subjected to a experience group x type of central target (2 x 2) mixed ANOVA.

A main effect of experience group was noted ($F(1,58) = 7.4$, $MSe = 123.5$, $p < 0.05$, $\eta_p^2 = 0.11$), with lifeguards correctly responding to more central targets than non-lifeguards (85.2% vs. 69.6% respectively) (see Figure 31). A main effect was also found for the type of central target ($F(1,58) = 7.7$, $MSe = 290.7$, $p < 0.05$, $\eta_p^2 = 0.12$), with more of the non-drowning targets correctly rejected than the drowning targets correctly identified (78.1% drowning targets vs. 86.7% non-drowning targets). The interaction between group and type of central target did not reach significance.

Next, the responses to the peripheral targets were analysed. A response was noted as correct if a response was given in the correct location and eccentricity. The accuracy of responses was converted into percentages and subjected to a experience group x eccentricity of peripheral target (2 x 2) mixed ANOVA.

Though the lifeguards appeared to successfully detect more of the peripheral targets than non-lifeguards (73% vs. 68% respectively) this difference was not significant ($F(1,58) = 1.13$, $MSe = 653.36$, $p = 0.291$, $\eta_p^2 = 0.02$) (see Figure 34). The main effect of eccentricity also failed to reach significance levels.

The interaction between experience group and the eccentricity of peripheral targets was also not found.

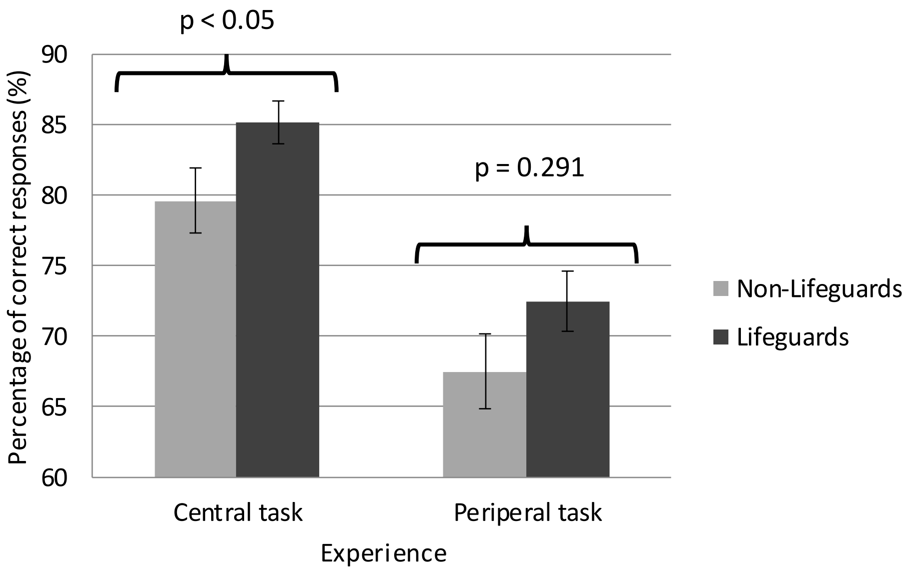


Figure 34. Average of correct responses to the FFOV central and peripheral tasks (with standard error bars).

5.4.2.1 Signal detection theory for FFOV

The measures of *d'* and *c* were calculated for each participant on their central task performance. These measures combined the hit rate for each participant across all drowning swimmers and compared them to the number of false alarms, where participants reported a drowning swimmer in catch trials.

An independent *t*-test compared these SDT measures across the two experience groups. Lifeguards were found to have higher sensitivity to drowning swimmers than the non-lifeguards ($t(58) = -2.69$, $p < 0.05$), with *d'* of 2.34 and 1.95 respectively, meaning they are morely likely to detect the drowning target. There was no difference between the experience groups in terms of criterion values ($t(58) = 1.28$, $p = 0.207$), with criterion values of 0.24 for non-lifeguards and 0.09

for lifeguards, suggesting there is no difference between participants' likelihood to say 'yes' to the signal.

5.4.3 Occlusion study

Responses to the occlusion drowning detection study were then analysed, this was done to make sure that there really was a difference between experience groups in terms of their ability to detect drownings and to act as a criterion variable for a regression.

The response rates to non-drowning trials were assessed first for the occlusion drowning detection data. On average non-lifeguard participants made an incorrect response to 30% (SD = 29.5%) of trials, while the lifeguard participants made an incorrect a response to 17.8% (SD = 28.7%) of trials. There was no difference in the number of trials successfully avoided between non-lifeguards and lifeguards ($t(58) = -1.63$, $p = 0.11$).

Correct responses to drowning-present trials were then assessed. Trials with a drowning target were considered incorrectly responded to if a response was made to an incorrect location, or a no drowning response was made. The trials that were correctly responded to were then converted into percentages. On average lifeguard participants responded to 67% (SD = 22.3%) of drowning targets, while the non-lifeguards successfully responded to 36% (SD = 19.4%) of drowning targets ($t(58) = -5.74$, $p < 0.001$).

The number of incorrectly missed drowning trials were analysed next. Trials where participants responded with 'no drowning' to drowning present trials were considered to be missed targets. These no-drowning responses to target present trials were converted into percentages and subjected to an independent samples t-test. On average lifeguard participants incorrected dismissed 23.7% (SD = 16.3%) of drowning present trials, while non-lifeguards incorrectly dismissed 42.0% (SD = 19.4%) of drowning present trials ($t(58) = 3.97$, $p < 0.001$).

The number of incorrect location responses during drowning present trials was then calculated. On average lifeguards made incorrect location responses on 9.3% (SD = 13.1%) of drowning present trials, while non-lifeguards made false alarm responses on 22.0% (SD = 14.9%) of drowning present trials ($t(58) = 3.49$, P = 0.001)

Signal detection analysis showed a significant difference between d' scores ($t(58) = -4.87$, $p <0.001$), with lifeguards demonstrating a higher sensitivity than non-lifeguards (1.15 vs. 0.003, respectively), suggesting that the lifeguards have a higher rate for detecting the target. There was no difference between *C* scores ($t(58) = 1.67$, $p = 0.101$)(lifeguards' score: -0.71 vs non-lifeguards' score:-0.51).

5.4.4 Multiple regression for the experimental data

A regression was performed for the experimental data, with the accuracy of drowning detection in the occlusion task as the dependent variable and FFOV performance on the central targets, FFOV performance on the peripheral targets, the time that MOA was maintained, and the mean number of balls achieved on the MOA task as the predictor variables. The means and SDs for each variable can be seen in Table 11. The correlations in Table 11 show that all 4 predictor variables are positively correlated with drowning detection, and central FFOV is highly significant.

There was a good fit between the predictor variables and the dependent variable (multiple R = 0.46) with the adjusted R^2 showing that the predictor variables explained 41% of the variance in the accuracy of detection of the drowning swimmer. The overall relationship was highly significant ($F(5,54) = 9.18$, $p < 0.001$).

Table 11. The means and SDs of the dependant variable and the predictor values and the correlation matrix.

Variable	Mean	SD	1.	2.	3.	4.	5.	6.
1. Experience group	1.50	0.50	1					
2. Occlusion	51.50%	25.96	.602**	1				
3. MOA Balls	4.85	0.70	.345*	.290*	1			
4. MOA Time (Seconds)	24.21	7.08	.338*	.299*	.977**	1		
5. FFOV Central	82.41%	8.27	.337*	.424**	.133	.120	1	
6. FFOV Peripheral	70.02%	18.09	.138	.284*	.141	.193	-.026	1

Notes: *P < 0.05, **P < 0.001

While there is a significant correlation between the predictor variables and drowning detection, an analysis of the unstandardized coefficients showed that FFOV central (Beta = 0.83, $t(54) = 2.48$, $p = 0.016$) and experience group (Beta = 24.15, $t(54) = 4.12$, $p < 0.001$) were the only significant predictors of drowning detection in the occlusion task see Table 12). The standardised coefficients showed that FFOV central (Beta = 0.265) and experience group (Beta = 0.469) were strong predictors of accuracy in detecting the drowning swimmer, with FFOV central target and experience group demonstrating a positive association.

Table 12. Summary of simple regression analysis for variables predicting drowning detection accuracy in the occlusion task.

Variable	B	*SE B*	*β*
Constant	-56.95	53.68	
Experience group	24.15	5.85	.469**
MOA Balls	-7.86	17.81	-.213
MOA Time (Seconds)	1.05	1.77	.285
FFOV Central	.83	.34	.265*
FFOV Peripheral	.24	.15	.165

Notes: *P < 0.05, **P < 0.001

5.3.4.1 Lifeguards

To explore where this regression analysis differs between the two groups, a separate analysis was performed for each participant group. First, the lifeguard participants' data was explored, with the accuracy of drowning detection in the occlusion task as the dependent variable and FFOV central target, FFOV peripheral target and the time that MOA was maintained, and the mean number of balls achieved on the MOA task as the predictor variables. The means and SDs for each variable can be seen in Table 13. There was a good fit between the predictor variables and the dependent variable (multiple R = 0.33) with the adjusted R^2 showing that the predictor variables explained 22% of the variance in the accuracy of detection of the drowning swimmer. The overall relationship was significant ($F(4,25) = 3.03$, $p = 0.036$).

Table 13. The means and SDs of the dependant variable and the predator values and the correlation matrix.

Variable	Mean	SD	1.	2.	3.	4.	5.
1. Occlusion	67.00%	22.31	1				
2. MOA Balls	5.09	0.65	.054	1			
3. MOA Time (seconds)	26.58	6.50	.102	.968**	1		
4. FFOV Central	85.18%	6.81	.483*	-.059	-.020	1	
5. FFOV Peripheral	72.50%	16.02	.207	-.389	-.027	-.123	1

Notes: *P < 0.05, **P < 0.001

An analysis of the unstandardized coefficients showed that FFOV central (Beta = 1.65, $t(25) = 3.01$, p = 0.006) was a significant predictors of drowning detection in the occlusion task for the lifeguard participants. The standardised coefficients showed that FFOV central (Beta = 0.549) was a strong predictor of accuracy in detecting the drowning swimmer, with FFOV central target demonstrating a positive association.

5.3.4.2 Non-lifeguards

A separate multiple linear regression was then performed for non-lifeguard participants, with the accuracy of drowning detection in the occlusion task as the dependent variable and FFOV central target, FFOV peripheral target and the time that MOA was maintained, and the mean number of balls achieved on the MOA task as the predictor variables. The means and SDs for each variable can be seen in Table 14. The overall relationship was non-significant ($F(4,25) = 0.56$, p = 0.69).

Table 14. The means and SDs of the dependant variable and the predator values and the correlation matrix.

Variable	Mean	SD	1.	2.	3.	4.	5.
1. Occlusion	36.00%	19.40	1				
2. MOA Balls	4.6	0.68	.157	1			
3. MOA Time (seconds)	21.83	6.93	.137	.978**	1		
4. FFOV Central	79.64%	8.78	.216	.069	.026	1	
5. FFOV Peripheral	67.53%	19.91	.156	.209	.297	-.049	1

Notes: *P < 0.05, **P < 0.001

An analysis of the unstandardized coefficients showed that there were no significant predictors of drowning detection in the occlusion task for the lifeguard participants.

5.5 Discussion

5.5.1 MOA

The results of Experiment 6 have supported the prediction that lifeguards will be better at avoiding multiple objects compared to non-lifeguards. The lifeguards were able to avoid more balls than non-lifeguards and for a longer period of time. It was expected that the lifeguards would do better in this task as it relates to their everyday role of supervising a number of moving swimmers around the pool. The MOA task is thought to elicit more eye-movements from participants than a traditional MOT task (Mackenzie & Harris, 2017). This fits with the results of research conducted by Wolfe, Place and Horowitz (2007) who suggested that visual tracking in the real world differs from typical laboratory studies, in that objects often move in and out of the area of focus. The results of their study found that observers were able to track an average number of 3.2 disks that moved in and out of the tracking set. It was also noted that tracking performance was unaffected as the items were added and subtracted from the tracked set.

While there was a significant difference between lifeguards' and non-lifeguards' responses on the MOA task, the performance on multiple object avoidance was not found to be a significant predictor of performance on the drowning detection occlusion task. Neither lifeguards' nor non-lifeguards' responses on the MOA task were associated with performance on the occlusion task. Although lifeguards were significantly better at avoiding a higher number of moving items, the results did not support the prediction that MOA would be a contributing skill in drowning detection, as lifeguards need to keep track of where people are when swimming in the pool. This result interestingly differs from previous research that has found performance on dynamic tasks to be linked to better performance on multiple object avoidance (Mackenzie & Harris, 2017). It may be that lifeguards have developed skills in tracking multiple moving objects from scanning pools full of swimmers, where they track for events such as the movements of identified at risk swimmers, people entering and exiting the pool or tracking numbers in the pool. However, this may not be a skill that will necessarily help in the detection of a drowning swimmer. To be able to recognise a swimmer in distress, the searcher may need to apply explicit attention to the behaviour being displayed by the swimmer to detect a drowning, rather than just tracking the movements of swimmers.

5.5.2 FFOV

In addition to the lifeguard superiority in the MOA responses, lifeguards were also found to be superior in their responses to the central target of the Functional Field of View task, with more accurate responses from the lifeguards than the non-lifeguards. The FFOV task in this experiment required the participant to make a response to a central target that is either swimming/playing or is drowning/distressed. As well as the central target, a peripheral target also appeared in one of eight locations. Previous findings have noted experts in a certain domain to have a larger field of view, detecting both central targets and peripheral targets more accurately (Crundall, Underwood & Chapman, 2002; Crundall, Underwood & Chapman, 1999).

While the lifeguards were found to be more accurate in their responses to the central targets, it was also expected that lifeguards would have a larger field of functional view, detecting more of the peripheral targets compared to the non-lifeguards. However, no difference between the two participant groups was found in the responses. This goes against previous research that suggests experts have greater detection of central targets and peripheral targets. Crundall et al., (1999) found in an FFOV study that expert drivers have a greater ability to detect the target in peripheral vision than novice drivers, who often have a degraded field of view. One potential explanation for failure to find a group difference between lifeguards and non-lifeguards in the current set of experiments is that the task of detecting peripheral squares is an irrelevant task for lifeguards, thus they dismissed that task and prioritised the central drowning swimmer. If the peripheral target related to a swimming pool environment, the lifeguards may have in fact engaged a wider field of view to take in more of the screen and engaging with the peripheral target more often. Alternatively, it may be that the non-lifeguards adopted a strategy where they focussed on the easier context-free peripheral task, with lifeguards only detecting 5% more of the peripheral targets than non-lifeguards. It may be that with a more difficult set of peripheral targets the lifeguards may show a wider field of view that would be expected in a swimming pool environment. For example, using a set of peripheral targets that are related to the swimming pool or possibly displaying the peripheral targets on swimming-pool background similar to the driving research presented by Crundall et al., (1999).

It was expected that responses to the FFOV task would be associated with performance on the drowning detection task. The lifeguards' responses to the central target were the only ones significantly associated with performance on the drowning-detection task. This suggests that the lifeguards are able to accurately process the central swimmer as either drowning or not, and this is potentially a skill that contributes to lifeguard surveillance. If a lifeguard is able to scan a zone of water, quickly processing the swimmers in the pool and the behaviour they are displaying, they may then be able to detect drowning swimmers more often and quicker than someone who has no experience with swimming and drowning/distress characteristics. In contrast the non-lifeguards' performance on the FFOV task was not found to be significantly associated with their performance on the drowning detection task. There is previous research which has demonstrated that experts within certain domains have shorter processing times of search items, such as experienced drivers compared to novice drivers (Gegenfurtner et al., 2011). This further suggests the processing of the drowning characteristics contributes to the lifeguards' superior performance on the drowning detection task and in future studies it may be interesting to explore how a training tool using drowning characteristics in a perceptual processing task may improve overall drowning detection.

5.5.3 Drowning detection task

Finally, the results of the drowning detection task using the occlusion method have confirmed the superiority of lifeguard drowning detection, with the lifeguards detecting more drowning and distressed swimmers than the non-lifeguards. This confirms the experience effect of lifeguards in these dynamic, naturalist scenes. This result mirrors those found in Experiment 5, which used a longer version of the task. The *Cohan's d* showed that the effect size for this shortened version of the occlusion task using the most discriminative clips was higher (1.48) compared to the longer version used in Experiment 5 (1.13). Furthermore, the results also add to the consistent finding from the experiments presented in Chapters 3 and 4, which demonstrate the accuracy of lifeguard responses to drowning events. The results of the occlusion task in Experiment 6 also fit with previous research exploring expert effects of surveillance type searches of dynamic scenes (Laxton & Crundall., 2017, Howard et al., 2010).

The responses to the central target in the FFOV task were found to be the only significant predictors of responses to the occlusion task, while responses on the MOA and peripheral FFOV task were non-significantly associated. This result suggests that one of the contributing cognitive skills that drive drowning detection is the recognition and processing of characteristics associated with drowning. This would fit with similar research that has explored processing skills in expert tennis players, which suggested that players need to have faster processing skills to improve performance during games and these faster processing skills results in player identifying the ball sooner, following its flight path and responding with appropriate motor responses (Paul et al., 2012). Perceptual learning has also been used to improve recognition of vehicles at road junctions, again demonstrating the benefits of processing skills in real-world search tasks. Crundall, Howard and Young (2017) found that perceptual training for the recognition of motorcycles improved participants' ability to detect oncoming motorcycles at road T-junctions. It may be that in future research drowning detection could be trained through a perceptual learning task.

One addition to the methodology of this study would have been to explore the Multiple Object Avoidance within a pool setting, similar to that of the Field of Functional View task that was employed. In the FFOV task, the central target was a 3 second video of either a swimmer or a real drowning incident, with participants needing to distinguish between the two types of target. A similar link to swimming could have been used of the MOA, with the moving balls superimposed over a swimming pool background. This could have made the task more relevant for the lifeguards, resulting in greater distinction between the two participant groups. However, it could be argued that results of the simple display of the MOA task should carry over into the real world setting of tracking swimmers around the pool, as it is the mechanism of moving overt and covert attention rather than the swimming pool environment that is important. Despite this possibility, the main aim of this experiment was to see whether there are underlying domain-free skills that relate to lifeguards. Domain-free MOA does relate, but it does not predict lifeguard skill. Domain-free peripheral processing did not show much difference between the participant groups in the FFOV task. The only part of the experiment that was not domain free was the central FFOV task, which showed the superiority effect between lifeguards and non-lifeguards and this predicted occlusion performance. Therefore, the lifeguards appear to have domain-specific processing abilities that lead to better drowning detection.

5.6 Conclusions

This experiment aimed to explore if two domain-free skills may contribute to superior lifeguard performance. The results show that lifeguards perform significantly better at MOA and the central task of the FFOV when compared to non-lifeguard participants. However, only performance on the FFOV central task was associated with performance on a drowning detect test in the lifeguard participants, and this was the only part of the two tasks that was not domain-free. These results suggest that lifeguard drowning detection is mainly driven through the ability to process the behaviours of drowning swimmers quicker than non-lifeguards. Therefore, it may be possible to train novices' visual search for drowning swimmers through an exposure task that increases perceptual processing of drowning behaviours. This possibility will be explored in Chapter 6.

Chapter 6
Intense classification training to increase the ability to detect a drowning swimmer

Research in the earlier chapters has shown a consistent experiential effect, with lifeguards detecting drowning swimmers more often and faster than non-lifeguards. The previous chapter also demonstrated that the ability to process the characteristics of a drowning target appears to predict drowning detection performance, suggesting foveal processing to be key in this task rather than visual search *per se*. The next chapter will explore if this superior detection can be trained through a training task that will improve foveal processing of drowning features. This will be based on previous perceptual-training tasks in different domains, with gamified features, that have been shown to improve detection of real-world items. The aim of this chapter is to investigate whether a training task to improve processing of drowning characteristics would improve drowning detection scores in non-lifeguards. The literature relating to perceptual training and training of processing speeds is discussed, with a focus on how perceptual training can be used to positively impact real-world scenarios, such as lifeguards' abilities to detect drowning swimmers.

6.1 Introduction

To recap, lifeguards spend a significant amount of time supervising a zone of water. Their primary role is to observe swimmers, to ensure safety and prevent drowning. Therefore, lifeguards are always on the lookout for characteristics that are related to behaviours of drowning, such as the *instinctive drowning response* (Pia, 1974). Despite surveillance being a primary component of lifeguards' jobs, there is little focus on surveillance skills in lifeguard training (Lanagan-Leitzel et al., 2015). For example, within the U.K. pool lifeguarding qualification, only a few pages are dedicated to surveillance in the training manual and there are currently no practical assessments for scanning and drowning detection. This limited training may be a result of the lack of research in the domain, which could be used to inform training and assessments.

Although lifeguarding has received limited focus in research, lifeguard surveillance has similarities to visual search tasks in other real-world domains. Domain specific search areas, including airport security, radiology and driving (Biggs & Mitroff, 2014; Nodine et al., 2002; Crundall, 2016) have shown key factors can help explain the differences between experienced and novice individuals within those domains. These factors can have a negative impact on visual search, and there is evidence to suggest that training can improve visual search and subsequent processing to overcome these issues (Krzepota et al., 2013; Guznov et al., 2017; Crundall et al., 2017). Would similar training mechanisms be useful in training lifeguards in their surveillance skills to detect drowning swimmers?

6.1.1 Natural perceptual learning

It has been well documented in research that speed of processing is one difference between experts and novices in regard to their visual-search performance, which could be trained in order to improve target recognition (Konstantopoulos et al., 2010; Underwood et al., 2002; Chapman & Underwood, 1998). Gegenfurtner et al., (2011) have suggested that experts tend to have shorter fixations on target items and this effect is reported to happen in many different domains, including sports and medicine. During some real-world visual search tasks, the speed of detection of visual stimuli is an essential factor for successful detection and fast responses to targets. For example, expert tennis players need to have fast processing skills to identify the ball, follow its flight and respond with the appropriate motor response all in a matter of seconds (Paul et al., 2011). In driving, research has demonstrated that experienced drivers have more efficient visual processing than novices, with shorter fixations on hazards (Chapman & Underwood, 1998).

A method of training object processing in visual search that has been documented in the literature is based on perceptual learning. Perceptual learning has been described as the increased sensitivity to features that define and discriminate relevant objects within a domain. This is argued to occur through sensory interaction with the environment or practice with specific sensory tasks (what we can see, hear, feel, taste or smell). These changes can have permanent or semi-permanent neural changes, with benefits in improved sensitivity to weak or ambiguous stimuli (Gold & Watanabe, 2010). Perceptual leaning is also argued to occur naturally in some real-world environments where individuals interact with certain stimuli and environments on a regular basis, sometimes over many years. For example, medical professionals, who have many years of experience examining x-ray images, have been found to have more sensitivity when detecting low contrast dots on x-ray images compared to novices (Sowden, Davies & Roling, 2000), or people who have familiarity of big brand labels have been shown to have faster recognition of familiar labels than unfamiliar labels (Qin, Kouststaal, & Engel, 2014).

Positive effects on visual search outcomes have been demonstrated through perceptual learning (Guznov et al., 2017; Schuster et al., 2013). For instance, Schuster et al., (2013) found that a discrimination based perceptual learning task improved performance in airport baggage surveillance. Furthermore, the benefits of perceptual learning are particularly evident when interactions between participant and stimuli are part of the learning process. Crundall, Howard and Young (2017) demonstrated this when they employed a pair-matching (Pelminism) game to increase recognition of motorcycles. The interaction between participant and stimuli in visual training results in long-term changes for the perception of the stimuli, with visual neurons changing (Kurylo et al., 2017; Li, Piech, & Gilbert, 2008). This suggests that the visual system is flexible, and can change as an individual becomes more experienced (Sagi, 2011).

Increased exposure to certain items is also believed to improve visual search performance and the detection of target items. In a real-world search task, where drivers were presented with videos of T-junction roads with an approaching car, a motorcycle or an empty road, Crundall et al., (2012) found that motorcyclists (who were also car drivers) were better able to detect approaching vehicles. These ‘dual drivers’ had longer gaze durations on motorcycles than upon the cars, and their fixations were longer than other drivers who did not ride motorcycles. This suggested that the dual drivers were more attuned to the image of approaching vehicles (including motorcycles which are much harder to see) and thus able to allocate attention to process the situation to make the right response. In contrast, the car-only drivers were more likely to fixate approaching cars than motorcycles, and in some cases fixated the motorcycle, but reported the road to be clear making a *look but fail to see* error. This finding seems at first to go against previous research that has suggested that experts have shorter fixations durations to domain items (Gegenfurtner et al., 2011; Underwood & Chapman, 1998). However it is likely that the quicker processing of the approaching vehicle allows the participant to identify it as a possible danger and continue to monitor it.

6.1.2 Perceptual training using discrimination tasks

Rapid visual exposure to stimuli has been argued to lower the threshold of identification (flash recognition training, Soule, 1958), but more recently researchers have focused on using discrimination tasks to train participants to process target features.

Perceptual learning tasks aim to improve visual processing of target items based on the idea that domain experts tend to be as fast at categorising superordinate classes of specific items as they are a categorising objects at a basic level. For example, a bird-watcher might be able to identify the ‘chaffinch’ when presented with two pictures of different birds, as quickly as if they were presented with a picture of a chaffinch and a cat (see Figure 35), whereas a non-bird-watcher will be slower when categorising at a subordinate level. Grill-Spector and Kanwisher (2005) suggest that basic level processing occurs before sub-ordinate processing. However, training people in sub-ordinate categorisation increases exposure to the super-ordinate category and is likely to lead to a refinement of a super-ordinate template. Therefore, training in sub-ordinate categorisation should result in more accurate and faster identification of target items even at a super-ordinate level.

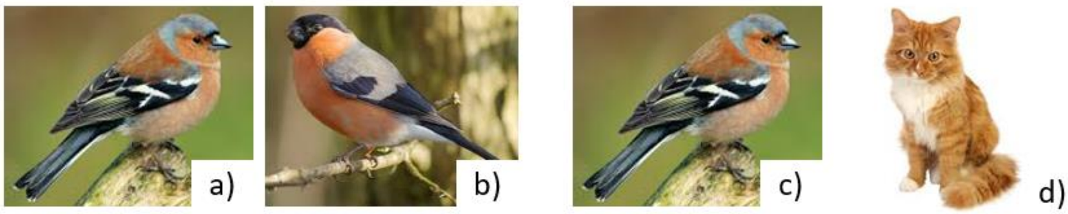


Figure 35. An expert bird watcher would be able to identify the chaffinch (a) from the bullfinch (b) as quickly as they would be able to identify the chaffinch (c) from the cat (d).

While the previous studies in this thesis have supported the argument that lifeguards are better able to identify drowning swimmers in a pool than non-lifeguards, there is no evidence so far to suggest that perceptual training would improve detection. However, other types of real-world search tasks have explored perceptual training through discrimination tasks. For example, when investigating the different effects of training on a real-world visual search task, Schuster et al., (2013) explored perceptual learning interventions for searches of airport baggage surveillance with a discrimination task. Undergraduate novice-participants completed a 30-minute computer task, identifying if improvised explosive devices (IEDs) presented in two side-by-side suitcases were identical. The results of this study showed that this perceptual training had a positive impact on search accuracy and speed in detecting targets in a subsequent test of performance, with participants learning an effective strategy in the training period.

In a further example, Guznov et al., (2017) trained novice participants in order to improve their ability to spot military fuel trucks during an unmanned aerial vehicle flight. During training participants had to discriminate between target military fuel trucks and non-target trucks (see Figure 36 a & b). The results demonstrated that participants trained in target discrimination subsequently spotted more trucks and made fewer false-alarm responses. This training was superior to two other types of training: *cue training*, where they were trained to discriminate between military and non-military hangers (as the latter was likely to be co-located with a military truck), and spatial training, where they were encouraged to systematically search the scene.

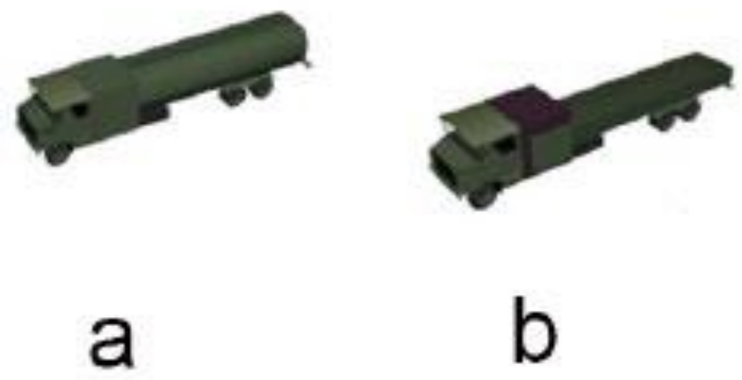


Figure 36. Target military fuel trucks and non-target trucks used as stimuli in Guznov et al., (2017).

6.2 Experiment 7

Based on the review of the literature, Experiment 7 aims to understand how lifeguard visual search can be trained in non-lifeguards (novices) through a short visual-processing training intervention. Non-lifeguards will be selected to explore if this training intervention can be used to improve drowning detection in complete novices.

Perceptual learning is argued to be trained through short tasks that require participants to discriminate between task related items (Guznov et al. 2017; Schuster et al. 2013). The findings of Experiment 6 also suggest that lifeguards are better at recognising and processing behaviours of swimmers once they have been fixated, rather than being able to apply a better search strategy (knowing where to look). Therefore, this experiment will train non-lifeguards to discriminate swimmers that are drowning from swimmers that are playing around in an intense discrimination task.

In all previous studies of perceptual training using discrimination tasks, the targets have been presented in isolation. In swimming, the dynamic context of other swimmers in the pool is likely to distract from the central task. Thus, presenting the drowning (or non-drowning) target in isolation seems appropriate here. However, if participants are solely trained on isolated target discrimination, then they may not be able to successfully transfer this training benefit to the more chaotic visual scene of a swimming pool with children at play. Accordingly, this training will start by presenting three blocks of targets for discrimination in complete isolation (i.e. only a small window of the swimming scene will be presented, containing just the target). However, the following three training blocks will use a slightly larger window in which to present the target, which will allow other potentially distracting swimmers to come into view. Finally, the last three blocks will contain an even larger window, with several more potential distractors in view. The target will always be in the centre of this window and participants will always know this. This gradual increase in window size across the training blocks creates a scaffolded approach to identifying drowning targets in ever-more realistic scenarios (by increasing the potential for distraction).

To explore if the drowning training has an effect on post-intervention drowning detection, an active control training task will also be employed. The control group will complete a training task that requires them to discriminate between indoor surfers ('Flowriders') who may, or may not, be about to fall over. The activity of surfing means that the instructions given to participants prior to the training are the same regardless of which intervention they are allocated to (looking for someone in trouble, not going to see something out of the ordinary for a lifeguard).

To measure the effect of the two training interventions (experimental and active control), a pre and post-intervention drowning detection test will also be used, and it is expected that the group who train on the drowning discrimination task will improve in their detection of drowning swimmers following the intervention. This is based on the idea that the superiority of lifeguards is primarily based on their ability to process and recognise drowning features once fixated, rather than knowing where to look, or picking up targets in peripheral vision. It is also expected that the group trained in the control task will not see an improvement in drowning detection in the post training task.

6.3 Method

6.3.1 Participants

Sixty-eight non-lifeguard participants were recruited to take part in a visual search training study for drowning detection (with a mean age of 21.71, 57 female). Thirty-four of these participants (mean age 21.42, 27 females) were randomly placed in the experimental task group, while the remaining thirty-four participants were placed in the control group (mean age 22, 30 female). Participants were recruited from advertisements on social media sites Linkedin, Twitter and Facebook, and from posters placed around the university campus.

6.3.2 Design

The study employed an independent group design in which subjects were randomly placed in either a drowning training intervention or control task intervention. The main dependent variable was the participants' accuracy of drowning detection in a post-training test, whilst controlling for pre-training test accuracy.

The presentation of the trials were randomised for all participants within a single block and the two blocks of stimuli used in the pre and post-intervention test were counterbalanced, so that 34 participants did the trials from one set of 13 clips (test A) first and the other 34 participants did the other set of 13 clips (test B) first.

6.3.3 Stimuli and apparatus

Stimuli for the pre and post-intervention assessments were taken from the stimuli of Experiment 5. Twenty drowning-present and six non-drowning clips were selected based on the responses of the 50 participants from Experiment 5, with clips that had the greatest difference between lifeguards' and non-lifeguards' responses being selected. Non-drowning clips were included to reduce participant guessing. The chosen videos were randomly placed into either test A or test B, and the order of these tests was counter balanced. The pre-intervention and post-intervention tests therefore contained 13 clips each, with 10 of those clips containing drowning targets.

New stimuli were created for the training and control interventions. For the control intervention video footage of Flowriders was downloaded from YouTube. Flowriding is a hobby or holiday activity where people can practice surfing in a contained area (a shallow tank of water with a flow of water coming from the front). The flow of water results in the Flowrider staying in the same position, which allows the use of a pool rather than a coastline. They are usually located in swimming pool complexes or on-board cruise ships. Twenty videos were selected of people who fall from a surfboard and a further 20 were of people who remain standing on the surfboard. Videos were cut to 3 seconds in length. For those Flowrider clips that led to a fall, the clips were cut to a point just before the fall (thus including cues to the Flowriders' instability).

For the drowning training intervention, the ten video clips from Experiment 5 that were not used for the pre/post-intervention test and ten new clips downloaded from YouTube[3] were used. Video clips contained either a drowning swimmer or fun swimming behaviours (e.g. splashing, handstands, jumping). There were 40 clips in total, twenty of each. The clips were also cut to 3 seconds in length.

Similar to the FFOV task used in Experiment 6, a small area of the swimming pool was presented on a grey background for each of these 3-second clips. This was achieved by placing a grey mask with an aperture cut out of it over the top of the full video clip. For the drowning training intervention, three different sized masks were used, with the target swimmer appearing in the centre (see Figure 37). As the size of the viewing window increased, more of the context could be viewed. In regard to the swimming targets, as the window increased in size, the number of visible distracting swimmers also increased. As the Flowriders did not have any additional context (apart from empty pool) one size of aperture was used for all of these control stimuli, as increasing the window size in the mask did not add any further complexity to the task (i.e. increasing the number of people appearing around the target; see Figure 38).

[3] (https://www.youtube.com/user/LifeguardRescue11/videos)

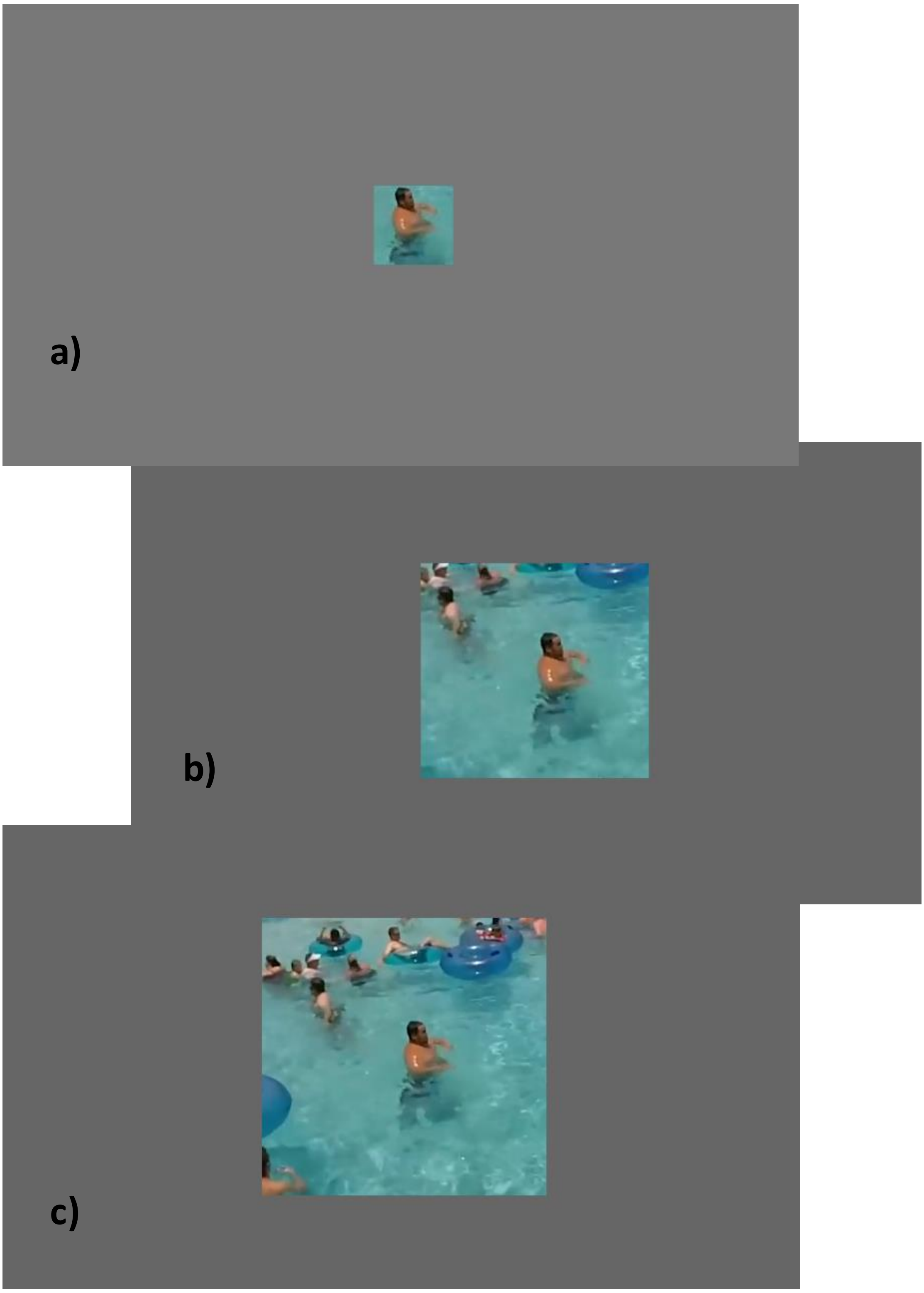


Figure 37. Three screenshots taken from the drowning training intervention of the same clip showing a) one swimmer in the central window of the small training round; b) the medium size window with the central target with potential distractors appearing; c) the largest window with more of the distractors. Participants completed three blocks of each sized window.

Figure 38. Two screen shots taken from the Flowrider training task displaying the one size mask with a surfer who may or may not be about to fall from their surfboard.

The presentation of stimuli in the intervention task was randomised for all participants within a single block. Blocks were repeated 9 times, and for the drowning training intervention, 3 blocks of each mask size was presented in order of smallest to biggest, in that participants completed three blocks of the smallest window, then three blocks of the medium window and finally the three blocks of training with the largest window. These were presented on a 1280 x 720 screen resolution. A central fixation cross was displayed before presentation of each trial for 500 ms and feedback presented after each clip. To add an element of gamification, correct feedback was presented in green and incorrect feedback was presented in red. After each training round, participants were presented with a percentage score for correct responses.

6.3.4 Procedure

Non-lifeguard participants were invited into the psychology department laboratory for pre-arranged testing sessions. Participants were given written instructions and asked to fill in a consent form and demographic questionnaire. Prior to the study the participants were made aware of the nature of the experiment and that they would see short clips that may be distressing, but nothing that a lifeguard would not face within a daily surveillance role. Once all instructions had been given, participants were given the opportunity to complete a practice trial for the pre-intervention test, which was followed by the chance to ask any further questions. When the participant was happy all questions had been answered, the main block of the pre-intervention test began. Upon finishing the pre-intervention test, the participants were then randomly assigned (without their knowledge) to either the experimental condition or the control condition and completed the 9 blocks of the training intervention, after a short practice. Each time 3 blocks of the training task had been completed, participants were given the opportunity to have a short break to refresh, thus in total 2 breaks were offered. Once the training intervention was complete, the participants then undertook the post-intervention drowning detection task. After successful completion, participants were fully debriefed and thanked for their time and participation. This research was conducted with approval obtained from Nottingham Trent University ethics committee and run in accordance with British Psychological Society guidelines.

6.4 Results

The data from 5 participants, 3 in the Flowrider training group and 2 in the drowning training group was removed due to a software crash. The data from one participant in the drowning training group was also removed due to that participant revealing that they had a current lifeguarding qualification. No outliers were identified, therefore the data from the remaining 62 participants was entered into an ANCOVA comparing the two training groups (Flowrider training and drowning training), while co-varying pre-drowning detection scores, in order to see if the different training tasks had an effect on post-intervention levels of drowning detection.

A significant effect was found for the type of training task on post-intervention drowning detection (ANCOVA, $F(1,59) = 13.63$, $P < 0.001$) (see Figure 39). The unadjusted means indicated that drowning detection was higher in the drowning-training group post-test scores (M = 61.0%) than with the Flowrider training group post-test scores (M = 45.5%).

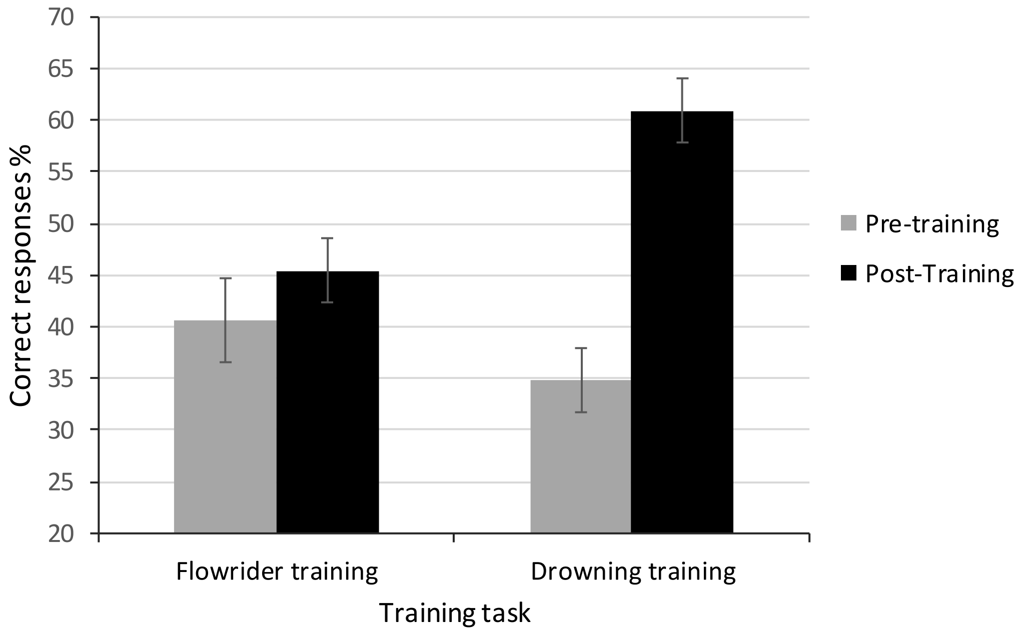


Figure 39. The average correct responses to drowning present trials across the post-training drowning detection test for the experiment and control groups. Pre-training drowning detection is included for comparison (with standard error bars)

Signal detection analysis showed a significant difference between d' scores ($t(60) = -2.31$, $p < 0.05$), with the drowning training group demonstrating a higher sensitivity than the Flowrider training group (1.00 vs. 0.62, respectively). There was no difference between *C* scores ($t(60) = 0.55$, $p = 0.582$) (Drowning training score: -0.55 vs Flowerider training score: -0.44).

6.4.1 Training analysis

The responses to the training blocks was analysed next. Data from 62 participants was entered into a 2 x 9 (training group x block) mixed ANOVA, to explore any difference in participants' responses over the 9 training blocks.

A main effect of training group ($F(1,60) = 11.31$, $MSe = 0.009$, $p < 0.01$) revealed that control training group made more correct responses than the drowning training group (94.8% vs. 92.2% respectively). The main effect of block was also significant ($F(1,60) = 20.65$, $MSe = 0.013$, $p < 0.001$).

The interaction between training group and block was found to be significant ($F(1,60) = 2.10$, $MSe = 0.002$, $P < 0.05$). Figure 40 appears to show that the drowning training groups' performance improved over each training round, however as the size of the training window increased at the start of each new training round (block 4 and block 7), performance decreased compared to the previous training block. The biggest increase in performance appears to be in the first training round, but the highest performance seems to be in the last block of the final training round. The Flowrider training group sensitivity appears to steadily increase over the 9 training blocks, with performance plateauing over the last three blocks.

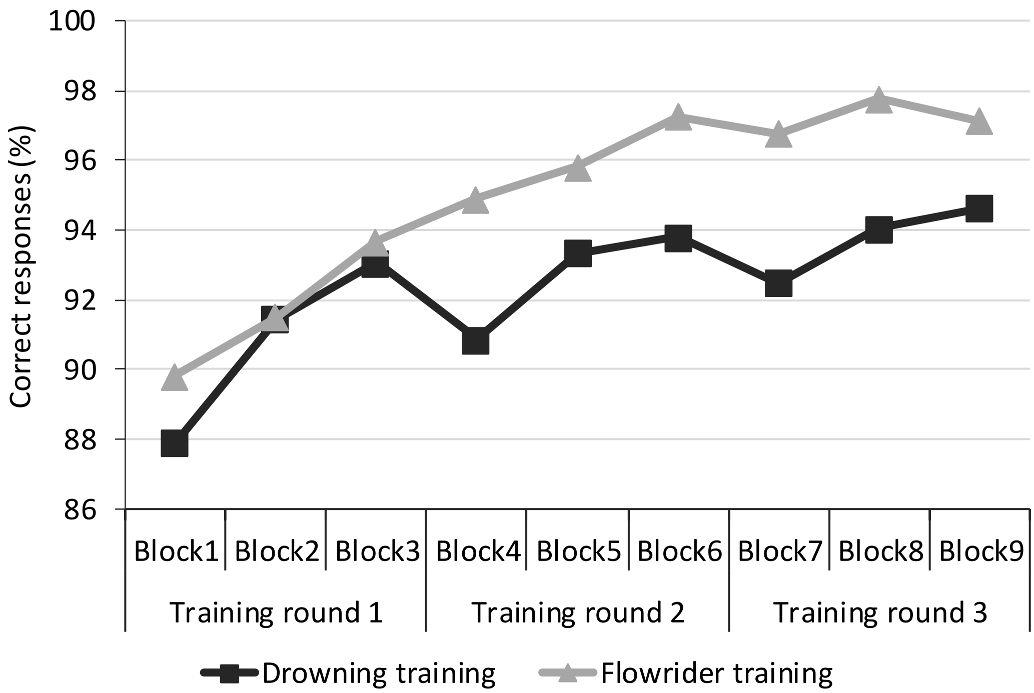


Figure 40. Average of correct responses in the training task

6.4.2 Signal detection theory analysis

The measures of *d′* and *c* were calculated to assess whether the improvement in participants scores across the 9 training blocks was due to a change in the sensitivity to the signal of a drowning swimmer, or a shift in the participants response criterion. These signal detection theory measures were calculated for each participant for all 9 training blocks and compared in a 2 x 9 (training group x training block) mixed ANOVA.

The *d′* measure was analysed first. There was a main effect of training group ($F(1,60) = 8.93$, $MSe = 1.09$, $p < 0.05$), with the group completing the drowning training having a lower *d′* score (2.98) and the Flowrider training group having a higher *d′* score (3.24). The main effect of block was also significant ($F(1,60) = 110.02$, $MSe = 0.296$, $p < 0.001$). This merely suggests that the cues to detecting an imminent Flowrider fall are easier to spot following practice.

The interaction between block and training group was also found to be significant ($F(1,60) = 5.10$, $MSe = 0.296$, $p < 0.05$). As can be seen in Figure 41, the sensitivity of the drowning-training group closely followed their percentage of correct responses (Figure 40): despite an overall improvement across blocks, as the size of the training window increased, sensitivity in the first block of each new training round decreased compared to the last block of the previous training round. The biggest increase in sensitivity appears to be in the first training round, but the highest *d′* score seems to be in the last block of the final training round. The Flowrider training group sensitivity appears to steadily increase over the 9 training blocks, with performance plateauing in blocks 8 and 9.

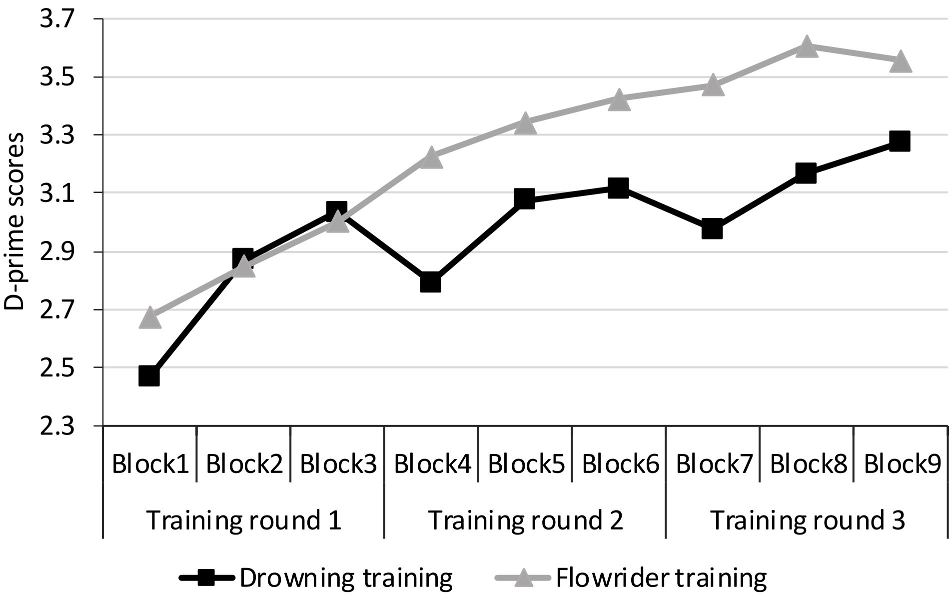


Figure 41. Average of d' scores to training task

The criterion value was analysed next. A criterion value was calculated for each participant for all 9 training blocks and compared in a 2 x 9 (training group x training block) mixed ANOVA. A main effect of group ($F(1,60) = 14.39$, $MSe = 0.093$, $p < 0.001$) revealed that the drowning training group had on average a positive criterion that was higher than the control group's criterion value (0.048 vs -0.05 respectively), meaning they are more likely to report that a target is drowning, while the Flowrider-trainees were more likely to report that the target would not fall. A main effect of block ($F(1,60) = 1.99$, $MSe = 0.028$, $p < 0.05$) also revealed a significant difference.

The interaction between block and training group was found to be significant ($F(1,60) = 5.10$, $MSe = 0.28$, $p < 0.001$). As can be seen in Figure 42 the drowning-training group criterion values appear to decrease over each training round, however the criterion values appear to increase again in the first block of the new training round compared the last block in the previous round. The biggest decrease in criterion values appears to be in the first training round, but the lowest criterion value seems to be in the last block of the final training round. The Flowrider training group criterion values appear to steadily increase over the 9 training blocks, with performance plateauing in the last training round (blocks 7, 8 & 9).

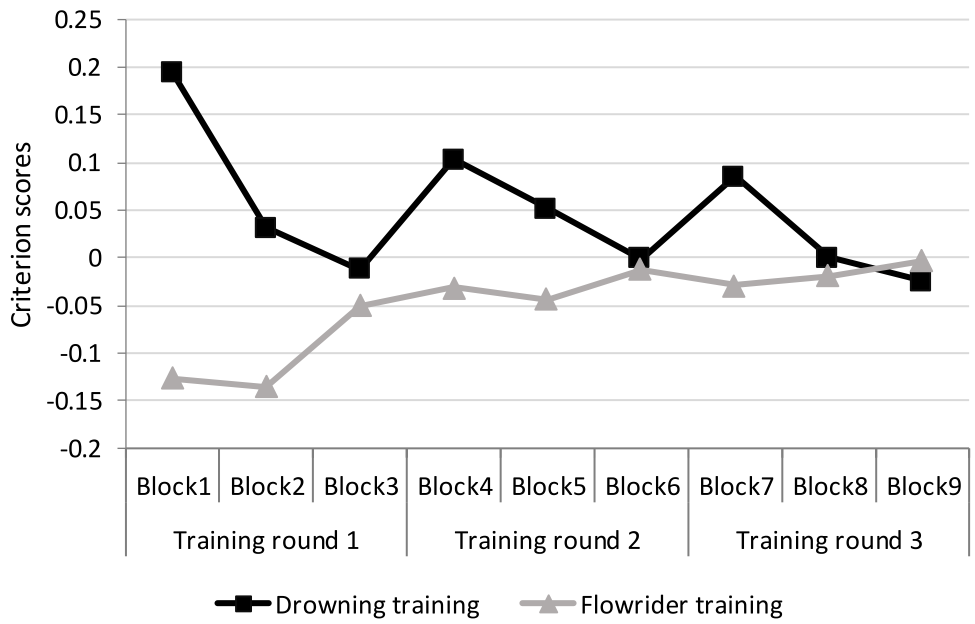


Figure 42. Average of criterion scores in the training task

6.5 Discussion

Experiment 7 attempted to improve non-lifeguards' (members of the public) ability to detect a drowning swimmer in videoed footage of a real swimming pool. This was achieved by employing an intense classification task where participants had to classify either a swimmer experiencing drowning/distress or a swimmer playing in the water. The rationale behind this was that the evidence from the literature and previous studies in this thesis suggested that central processing of the drowning characteristics is perhaps the key factor that underlies lifeguard superiority in drowning detection tasks. Interpretation of otherwise ambiguous swimming behaviours was improved by forcing participants to repeatedly and rapidly classify potential drowning characteristics. Furthermore, the gradual increase in the size of the training window, gently exposed trainees to a wider context, preparing them to use their new skill in a full-screen drowning detection task.

This task incorporated gamified features, such as feedback of responses given after each trial and scores after each block. A second group, the control group, had a similar intense classification task, which required participants to classify either a surfer about to fall of the board or remain standing on the board. It was expected that the drowning perception visual training task would improve drowning recognition.

The main results of this experiment showed that the participant group who received the drowning training significantly improved their ability to detect drowning swimmers in the post intervention task. This improvement in drowning detection may be a result of the repeated exposure and level of engagement in the drowning training task, which required participants to determine if the behaviours being displayed in a three second clip are those of drowning or not. This pattern of results could be explained by Ahissar and Hochstein (1996), who suggest that while some simple visual tasks can lead to an improvement in performance, any learning benefits from training require participants to engage with the stimuli. For example, in the current study, when people are repeatedly exposed to drowning characteristics, actively having to distinguish between drowning and distressed swimming behaviours or similar fun and play swimming behaviours in the task, their performance in drowning detection appears to improve to that of a similar level of the lifeguard participants in the occlusion study of Experiment 6.

Results similar to the improvement of the drowning training group after completing gamified tasks were seen in Crundall et al., (2017), where an experimental group of car drivers completed Pelmanism games that required them to match pairs of motorcycles. After playing these Pelmanism games to improve recognition of motorcycles, it was reported that the car drivers improved in their ability to detect motorcycles at road T-junctions in a computer-based detection task. It may be possible that these tasks (distinguishing different motorcycles or in this case drowning behaviours from fun swimming behaviours) require more scrutiny to accurately differentiate between events, and thus more learning takes place.

The results from the control task used in the Crundall et al., (2017) study also shows similarities to the results of the control task in the current experiment. Control participants in the Crundall et al., study were required to match pairs of fruit in the Pelmanism game, and were found to have no significant improvement in their detection of motorcycles at road T-junctions. In the current experiments, control participants did not show any significant improvement in drowning detection after completing an active training task, beyond a slight trend that is to be expected from practice on the pre-intervention assessment test. It is also interesting to note that performance in the control-training task, where participants had to distinguish if Flowriders were about to fall, also improved over the nine training rounds. Although the training did not lead to an improvement of subsequent drowning detection, this improvement over the training blocks does suggest that learning within the control-training task also took place.

Why did the drowning-training group's performance on the post-test improve? One possibility may be that the recognition task of a drowning swimmer used in the training task has improved their speed of processing. The exposure to drowning characteristics, with the active engagement in the task may have improved the drowning training groups' ability to process the visual information in the scene more quickly, leading to faster decisions in the drowning detection tasks when determining if a swimmer is displaying drowning behaviours. Previous research has shown that computer-based tasks and perceptual-learning tasks improve processing speeds, which can be transferred into real-world behaviours (Owsley, 2013; Yehezkel et al., 2016). Lev et al., (2014) employed a perceptual training task that used Gabor patches and letter crowding for foveal vision in reading on smartphones. They found that processing speeds were improved in young adults, and these improvements generalised into other visual functions, such as detection in crowded searches. If this is applied to the training interventions used in this current study, then it may be expected that the processing of the central target in both tasks could have some positive influence on drowning detection in the post-intervention occlusion task, with processing speeds improving general visual functions as in Lev et al. However, any carry-over effects of visual processing were not transferred from the Flowrider training task, therefore it is more likely that training using the specific drowning characteristics is of key importance.

One of these possible factors that could have led to better performance in the drowning training group's post-training drowning detection task is the exposure to different drowning-behaviours. This exposure could result in greater sensitivity to drowning characteristics and is likely to result in faster processing of the target. Findlay and Walker (1999) suggests a model of saccade generation that may help understand how this visual processing of drowning swimmers works. In this model there are two factors at play. First, the *fixate* centre encourages the eyes to stay on the target and process it for longer. Second, the *move* centre is concerned with maintaining active visual search, and therefore does not want to leave the eyes in one position for too long. There is a reciprocal inhibitory link between the two, and as information is identified from foveal processing to show that the point of fixation is likely to contain a drowning target, this inhibits the urge to keep moving the eyes. If foveal features are processed quicker, then it is more likely to get enough information to convince the *move* centre to stop urging the eyes to move.

As drowning is a complex behaviour, with no person drowning in exactly the same way, it is difficult to know the exact behaviour of a swimmer in distress. Consequently, learning and exposure to a variety of drowning behaviours may improve general knowledge of target behaviours and features by forming general target templates. Thus, when searching for distressed and drowning swimmers the knowledge forming general target categories may help visual processing of the swimmers in the pool and result in faster identification of the target behaviour (drowning and distress) and correct dismissal of play behaviours that share some similarities to drowning swimmers (floating or jumping up and down off the pool floor). It is likely that this target knowledge helps the observer realise that they are looking at something important and stops them from moving on (Findley & Walker, 1999).

It is interesting to note that the drowning-training group's sensitivity to the target increased over the 3 blocks for each mask window size, but each time the window increased from one size to the next size up, performance decreased slightly. This suggests that isolating just a single swimmer on the screen allows the participant to become familiar with differences in drowning characteristics and similar fun swimming behaviours. However, as more swimmers are introduced, the task initially becomes harder in the first block of a new sized window in the mask, but as participants become more experienced throughout training, drowning detection once again becomes easier. The increasing window size is a way of gradually exposing trainees to a wider context, preparing them for processing targets in the real (unmasked) world. It is understandable that an increase in context sets back performance, but the gradual approach appears to encourage trainees to persevere. It would be interesting to compare the scaffolded approach to drowning detection in wider contexts and to explore just using the large window or just using the small window. With 9 blocks of the small window one might expect even better performance over the 9 blocks (with no regressions in performance at block 4 and 7). However, it would be unlikely that performance in the post-intervention drowning detection task be as good.

Alternatively, 9 blocks of the large window would also be unlikely to show any regressions in performance, but training performance is likely to be much lower, and participants may become disheartened early on. Again, it is possible that post-intervention performance on the drowning detection task would not be as good as that of the scaffolded approach.

It should be noted that all training clips used for the drowning training task were taken from the same swimming pool environment as the pre and post-training test video stimuli, which may influence how drownings are recognised within these clips. It could also be argued that the similarity of testing and training contexts does have an effect on the outcome of training. This could be explained by near/far transference of training (Barnett & Ceci, 2002; Sala et al. 2019; Zelinsky, 2009). The similar context of the drowning-training task would fall into near transfer, where the training is highly specific to the subsequent testing. It is not clear if this drowning-training would transfer to other pools (far transfer). In future research it would be interesting to see if training effects carry over into other swimming pool settings, however, this is difficult to test without access to naturalistic stimuli in another pool.

6.6 Conclusions

This study has been one of the first to illustrate the potential benefits of using a perceptual processing training task to improve drowning detection rates. Results suggest that the two training tasks (Flowrider fall recognition and drowning recognition) both encouraged perceptual learning, though only the drowning training improved non-lifeguard responses to a post-training drowning detection task. Therefore, this preliminary research into training lifeguard visual search suggests the potential effectiveness of using this type of visual training for new lifeguards and lifeguards completing top-up training. Future research should consider if this type of training translates into other pool environments. General implications and the limitations of this research are explored in the General Discussion of this thesis.

Chapter 7
General Discussion

This final chapter will offer further discussion of the results found in each of the experiments, with particular focus on the potential theoretical and applied implications for the findings, possible future experimental directions and the limitations to the studies. This section, and with it the thesis, will end with general conclusions and assessment of the original contributions to knowledge for this thesis as a whole.

7.1 Introduction

The central aims of this thesis were to investigate whether lifeguards have superior visual search skills in detection of a drowning swimmer, and, if so, whether these visual search skills in drowning detection can be trained. The introduction chapter reviewed previous studies that are of importance to this thesis and identified a number of limitations, such as the use of static scenes and contrived, or low-fidelity, stimuli within the limited applied lifeguarding research. Although there are a considerable number of studies that have explored visual search in real-world settings (Biggs & Mitroff, 2014; Drew et al., 2013; Gong et al., 2018; Peelan & Castner, 2014), which have identified clear experiential effects (Bertram et al., 2016; Curran et al., 2009), there is considerably less evidence for the effects of experience in applied-dynamic visual scenes, particularly for the expert domain of lifeguarding. This is surprising given the importance of pool supervision and the grave consequences when failures in this supervision occur.

Of the limited prior research that has investigated the role of visual search in lifeguarding, a number of limitations have been noted, such as search stimuli being presented in highly controlled laboratory settings, with low-fidelity computer-generated items (Page et al., 2011) or naturalistic stimuli, with recorded footage of swimming activity (Lanagan-Leitzel & Moore, 2010). Consequently, the highly-controlled artificial stimuli used in Page et al. (2011) make it difficult to generalise any findings back to a beach and pool setting, while the natural videos of pools and lakes used in Lanagan-Lietzel and Moore (2010) suffer from a lack of experimental control, which make it difficult to conclude anything. This thesis presented a novel and original approach to these issues. Over a series of 7 experiments, the detection rates for drowning swimmers were measured across differing experience levels, from non-lifeguards to lifesavers, lifeguards and lifeguard trainers, in a variety of visual search tasks. The first 2 experiments in Chapter 3 explored drowning detection rates to videoed incidents of simulated drowning while the experiments of Chapter 4 employed videos of real drowning incidents captured in an American wave pool. The final two experiments explored the nature of lifeguard visual search skills through investigation of contributing cognitive mechanisms, and how these can be used to create an effective training tool to improve drowning detection in future lifeguards.

7.2 Summary overview of findings

Recent evidence has shown lifeguard expertise in visual searches when looking for critical behaviours that could be linked to drowning and distress (Page et al., 2011; Lanagan-Leitzel & Moore, 2010; Laxton & Crundall, 2018). The results of Experiments 1-6 (Chapters 3, 4, & 5) were consistent with this lifeguard expertise effect in drowning detection tasks. In the experiments exploring reaction times and accuracy of responses (Experiments 1, 2, 3 & 4), an experience effect was noted with lifeguards responding faster to drowning/distressed swimmers compared to non-lifeguard participants. However, while lifeguard superiority was noted for the accuracy of responses, small differences were noted across the experiments. The results of Experiment 1 failed to find an *overall* effect of lifeguard superiority in their detection accuracy, though their expertise was apparent in the interaction with set size: Lifeguards detected more drownings than the non-lifeguards in set size 3 and 6. When the number of swimmers in the pool increased to nine, the highest set size in Experiment 1, the performance of the lifeguards and the non-lifeguards became comparable. These findings in Experiment 1 suggest that lifeguards are only superior in their life-saving search skills when there are fewer swimmers in the pool. While this ceiling effect for lifeguard superiority is understandable in terms of experimental design – as the demand increases experiential benefit is no longer effective – the absolute number of swimmers in the large set size (nine) is far below the number of swimmers that lifeguards would be expected to supervise. One would hope that lifeguard superiority in real settings continues beyond the limit of 9 swimmers, and that the ceiling in this study was artificially lowered due to the level of control exercised over the stimuli and task.

In Experiment 2 (Chapter 3), lifesavers and trainers were included as additional participant groups on the simulated drowning detection task employed in Experiment 1. The results of Experiment 2 found lifeguard superiority in the accuracy of responses, with the influence of training in drowning-behaviour knowledge apparent in the responses of lifesavers, lifeguards, and trainers. The three experience groups (with levels of lifeguarding expertise increasing from *lifesavers* to *lifeguards* to *trainers*) were found to have similar levels of accuracy in their correct responses to drowning swimmers, while the non-lifeguards were found to detect significantly fewer of the drowning swimmers. Although lifeguards, lifesavers and trainers had similar levels of detection accuracy, the response times between lifeguards and lifesavers differed, with the lifeguard group detecting the drownings around 600 ms faster than the lifesavers. Although the lifesavers detected drowning swimmers on average 500 ms faster than the non-lifeguards this difference only approached significant levels. The results of both Experiments 1 and 2 suggest that there is a positive influence of lifesaving training (which tends to be limited to the knowledge of drowning characteristics) in the detection of a drowning swimmer in this simulated task. As the lifesavers have a similar knowledge of drowning behaviours to lifeguards, it may be that this ability to recognise drowning behaviours is driving the similar levels of accuracy between the two groups rather than a greater ability in scanning the pool. Together with the equivocal eye movement findings in Experiment 1, this finding raised the possibility that knowing where/how/when to look around a pool (which lifesavers are *not* trained in) was less important to drowning detection than the ability to recognise the drowning characteristics (which lifesavers *do* receive training in).

While the simulated nature of the tests created for Experiments 1 and 2 were relatively naturalistic compared to previous controlled studies of lifeguard visual search (Page et al. 2011), the ostensible limitations of using a maximum of 9 regimented swimmers in such an artificial situation may not allow us to generalise the results to real situations. Accordingly, Experiments 3, 4 and 5 (Chapter 4) employed real video footage of swimming pools with clips of drowning or distressed swimmers. The results of these three experiments confirmed the superiority of lifeguard responses to real drowning and distress, with more complex scenes (increased numbers of swimmers in the pool). This was seen in both the accuracy of responses in all three experiments and in the response times in Experiments 3 and 4. The findings in these studies were similar to those found in Experiment 2 with lifeguards responding better to the simulated drowning swimmer than non-lifeguards, further suggesting that lifeguard experience is influencing search skills in more complex trials.

Experiment 5 employed an occlusion method in the drowning detection task. The rationale for this study was based on the possibility of biased responses caused by an ambiguous response time window in Experiments 3 and 4. Research has also suggested that occlusion methods are more robust than response time based tasks (Castro et al., 2014; Crundall & Eyre-Jackson, 2015; Ventsislavova et al., 2019). The median response times of the detection of the drowning swimming for the first 15 lifeguards and first 15 non-lifeguards in Experiment 3 were used to create an occlusion screen in the video clips. The results showed an experience effect of lifeguards' greater accuracy in responses to drowning swimmers after the scene has occluded. In a comparison between Experiment 3 (reaction time study) and Experiment 5 (occlusion study), the occlusion method of Experiment 5 appeared to show a greater effect size between lifeguard and non-lifeguard detection rates for the drowning swimmer than the reaction time based study employed in Experiment 3 (partial eta = 0.20 for 3 and partial eta = 0.43 for 5). Therefore, when looking into the different methods that explore lifeguard surveillance skills, it could be argued that the occlusion study might be the more robust method when exploring differences between trained and untrained groups for drowning detection. In this occlusion method, the lifeguards potentially have to rely more on their prior knowledge of drowning incidents and have to extract information from the scene faster to detect potential drowning swimmers.

In addition to the experience effect found across all experiments, a non-monotonic set-size effect was found in the first 3 experiments. In Experiments 1 and 2 the best accuracy responses were noted in the set size 6 condition (intermediate set size), but only for active drownings. This effect, found in the simulated stimuli, was also present in the responses to the naturalistic drowning video clips employed in Experiment 3, with the highest accuracy for responses found in the medium set size, which had between 39 and 52 swimmers in the pool. However, it appeared from the planned repeated contrasts of the interaction between set size and experience that the non-lifeguard participants were driving this effect. The non-monotonic set size effect, where accuracy of responses increased in the intermediate set size, did not appear in the occlusion study, suggesting that when the need for speeded responses are removed from the experiment, results follow an expected trend in performance, with accuracy decreasing as set size increases. It is unclear what is driving this peculiar set size effect. It may be a result of participants changing search strategy between the low and the medium set size, and this change in strategy rejuvenates search performance. A further possibility could be the possible differential effects of boredom/overload, where the lowest set size may not contain enough complexity in the stimuli to stimulate the searcher while the highest set size may contain too much to keep track of (please see later in the chapter for discussion of the Yerkes-Dodson law, 1908; Schaaff & Adam, 2007). The amount of activity in the intermediate set size may however be just enough to keep the participant engaged in the task, while not being too demanding on attentional resources.

In Experiments 1 and 4, eye-tracking measures were employed. The results showed that there were no differences between the lifeguards and non-lifeguards in the number of targets fixated, the time to first fixate the target, and the percentage of time spent looking at the target. This lack of difference was found in both Experiments 1 and 4. However, in Experiment 1, a '*looked but failed to see*' error is apparent for both lifeguards and non-lifeguards in the eye movement data (though more so for the non-lifeguard participants in the lower set sizes): Both lifeguards and non-lifeguards fixated a similar number of targets, but the non-lifeguards responded to fewer of them. Also, in set-size nine, both lifeguards and non-lifeguards fixated a large number of targets, yet still failed to identify the target (for example, 100% of passive targets were fixated by non-lifeguards but they only responded to 84% of them).

A post-hoc analysis for the location of the drowning was conducted for Experiments 3, 4 and 5 (Chapter 4), which used the real pool footage. Drownings that occurred closer to the camera were detected more often than drownings that occurred in the half of the pool further away from the camera. This effect was expected, and appears in all three experiments using the real drowning clips. In Experiment 3 an interesting interaction effect was noted between the location of the drowning and the set size of the trial. When the drownings were noted to be further away from the camera, a decrease in response times was noted at the intermediate set size. This effect appears to mirror that found in the accuracy of responses, with responses improving at the intermediate set size. It would be expected that as set size increased, the drownings further away from the camera would demonstrate a significant decrease in accurate responses and a corresponding increase in response times. In Experiment 5, an improvement in accuracy for detection of drownings that were further away from the camera was noted for the lifeguard participants at the intermediate set size. This effect, however, did not affect the overall detection for lifeguards, which followed a monotonic set size effect. This finding further demonstrates the complexity of naturalistic stimuli, and how responses may differ from more tradition visual search tasks.

Following these experiments, the subsequent chapter of the thesis set out to explore the cognitive processes that may contribute to the noted superior performance of the lifeguards in the drowning detection tasks (Chapter 5). Experiment 6 employed a Multiple Object Avoidance task (MOA) and a Functional Field of View (FFOV) processing task. A short occlusion task of the real drowning clips was also employed in this study. Lifeguard superiority was found in the MOA task, with lifeguards successfully avoiding more of the moving balls than non-lifeguard participants. Lifeguards were also found to be able to sustain the MOA task for a longer period of time. In the FFOV task, lifeguards were found to be better at correctly responding to the central target on the FFOV task than non-lifeguards (identifying if an isolated swimmer was drowning or not). It should be noted that this central task was not a domain-free cognitive skill, but a domain-based part of the skill used to identify whether the deployment of extra-foveal attention is impacted. In the peripheral task, no difference was found for the responses to the peripheral targets between lifeguards and non-lifeguards. A multiple regression was performed on the data, with MOA performance and FFOV performance on both the central target and the peripheral target as the predictor variables. The outcome variable was the accuracy of responses on a drowning-detection task using the occlusion methodology (which was undertaken at the same time as the MOA and FFOV tasks). Only the FFOV central target was a significant predictor of responses on the occlusion study. This again suggests that the most important skill for detecting drowning swimmers in highly complex scenes is the classification and recognition of the drowning behaviours and characteristics, with processing performance at the point of fixation underlying the superior performance of lifeguards in this visual search task.

Although lifeguards were better at the MOA task, this ability did not seemingly aid in the detection of drowning swimmers. It is not clear whether people who are naturally adept at tracking and avoiding multiple objects are attracted to the role of lifeguarding, or whether lifeguarding experience contributes to an underlying ability to perform on the MOA task. Regardless, there is no evidence to suggest that superior performance on MOA contributes anything to performance on the drowning detection task.

Based on the results of Experiment 6, the final experiment of this thesis, Experiment 7 (Chapter 6), assessed the effectiveness of a short training intervention on subsequent drowning detection. A discrimination-based perceptual task was chosen. This was based on the findings of the previous chapters pointing to lifeguard superiority being driven by their ability to process the drowning characteristics of foveated swimmers. In the experimental training condition, non-lifeguard participants were required to classify if a swimmer was drowning or not. Three different window sizes were used in this training, creating a scaffolded approach that gradually introduced the participants to identifying drowning swimmers in more realistic scenes (by increasing the potential of distractor items impacting on target processing). In the first round of training, three blocks were completed with a small window, where only one swimmer was visible. The next round of training had a slightly larger window, with more pool context visible (e.g. other swimmers, rubber-rings). The final round of training used an even larger window, again increasing the visible background context.

An active control task was also used, which required participants to classify if a surfer was about to fall off a board while engaged in the activity of Flowriding. The group who received drowning training was seen to significantly improve their drowning detection in the post-training occlusion task, with pre-training performance used as a covariate. In contrast, the control group's performance from pre-training to post-training drowning detection did not significantly improve.

During the training rounds on the drowning detection training task, signal detection measures of sensitivity where found to decrease at each new stage of the training rounds, between the last block of a smaller window and first block of a larger window. However, sensitivity was seen to increase over the three blocks in each training round, with sensitivity to drowning swimmers being at its highest in the last block of the last training round. In contrast, the active-control task saw sensitivity increase over the first two training rounds, but in the last round of three blocks, sensitivity plateaued.

Increasing the background information through different sized windows in the training task is an interesting feature in this experiment. While there is no evidence in the current study to suggest that this is crucial to producing the training effect, there is a logical rationale for its inclusion, and the importance of this aspect needs to be studied further. For instance, a study comparing 9 blocks of small window training vs. 9 blocks of the large window training vs. the 9 blocks of increasing size used in this study would allow the importance of the latter scaffolded approached to be assessed.

7.3 Summary conclusions

In light of the findings discussed above, the following conclusions can be drawn. First, experience effects in visual processing of dynamic, naturalistic stimuli can be seen in lifeguards when detecting drowning swimmers. This research has differentiated between trained lifeguards and non-trained controls over a variety of tasks and methodologies, paving the way for an assessment tool to ascertain skill levels of lifeguards, possibly as a barrier to overcome for entry to the job, or as a way of assessing the benefits of training interventions.

Second, the difference between lifeguard and non-lifeguard drowning detection did not appear to be driven by superior scanning, with no differences found in eye-tracking measures. Instead, the experiential effect appears to be due to processing of foveated swimmers (recognition of drowning swimmers at the point of fixation). Therefore, drowning detection is potentially associated with lifeguards' prior knowledge or exposure to behaviours associated with drowning and the ability to classify such behaviours, rather than any superior scanning skills. This would suggest that training people where to look would appear to be less important than improving lifeguards' ability to discriminate between drowning and non-drowning behaviours.

Third, the processing and discrimination of drowning from non-drowning swimmers at the point of fixation can be trained in novices with no prior experience of drowning behaviours or experience in conducting visual searches for drowning swimmers. This can be achieved through a foveal discrimination task, which exposes observers to short isolated videos of drowning and distress characteristics. This uses a scaffolded approach that increases the amount of background information over training rounds.

The remainder of this chapter will consider these main conclusions in more depth and in relation to previous findings, focussing on both theoretical and applied implications. There are also a number of outstanding questions that that will be addressed later in this chapter (section 7.6).

7.4 Set size and drowning type effects

Although lifeguard superiority of drowning detection has consistently been found throughout this thesis (Experiments 1 - 6), the role of a lifeguard is still complex and a number of challenging factors have been found to influence visual search for drowning detection in both the expert lifeguards and the non-lifeguards.

7.4.1 *Set size effects*

In Experiments 1 and 2 (Chapter 3), responses to an intermediate set size were noted to be better in active drowning conditions. This effect was also noted in Experiment 3 (Chapter 4), with the video clips containing real instances of potential drowning. However, in Experiment 3, it appears that this effect was driven by the responses of non-lifeguard participants. This non-monotonic set size effect has also been found in previous research (Laxton & Crundall, 2018), where active drowning trials received better responses at the intermediate set size with 6 swimmers, compared to when there was 3 or 9.

One possible explanation for the non-monotonic set-size effect is the level of stimulation and engagement the participant has with the drowning detection task. The Yerkes-Dodson law (1908; Schaaff & Adam, 2007) relates to early research that has proposed a relationship between arousal and performance, with different tasks eliciting different levels of arousal (see Figure 43). With regard to lifeguarding, drowning detection may be affected when the number of swimmers in the pool is too high or too low. Griffiths (2002) suggests that when the search of a swimming pool becomes monotonous, such as only having a few people in the pool, the lifeguards' attention and search performance is affected by boredom and task performance is decreased. However, Griffiths also suggested that high levels of arousal, such as busy fun sessions with lots of features also results in poor search performance from lifeguards. The high levels of stimulation with busy pools can easily lead to observers becoming stressed with more objects in the search zone to scan and monitor. For example, for lifeguards in Experiment 3, when there were between 20 and 40 swimmers in the pool (the low and medium set sizes) this potentially provided enough stimulation for them to remain focused on the task. However, when the number of swimmers increases to above approximately 60 (the high set size), the lifeguards may be come over stimulated and search performance suffers. In contrast, non-lifeguards may be under stimulated in the low set size, with targets being easier to spot and as the task not being related to their everyday work. Non-lifeguards may be more likely to lose focus in the lower set size as they become bored with the task. Whereas search performance may become rejuvenated in the medium set size, with the task becoming slightly more difficult and requiring more attention. The highest set size may see the task become too demanding with search performance negatively affected.

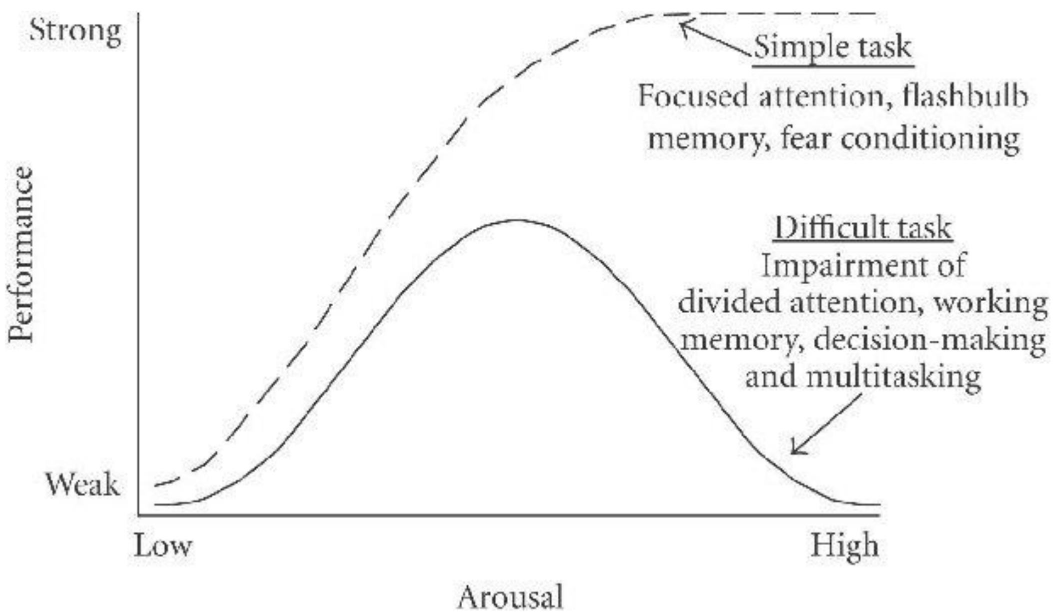


Figure 43. The Yerkes-Dodson Law (1908) where high arousal on simple tasks can be beneficial to performance. However, performance in difficult tasks can suffer in conditions of low or high arousal (adapted from Schaaff & Adam, 2007).

While the search stimuli differ greatly in terms of the set size between the experiments in Chapters 3 and 4, participants may rate how demanding each trial is relative to the overall demand of the entire study (Colle & Ried, 1998). Thus, nine swimmers may be considered a high demand when compared to three, but 20 swimmers would seem relatively easy compared to 60. This may explain why the non-monotonic effect occurs in both the simulated and naturalistic stimuli despite the difference in absolute numbers of swimmers between the two experiments. It should be noted that this non-monotonic set size effect was not found consistently throughout the thesis, with the effect lost in Experiments 4 and 5 (potentially due to changes in experimental design). These results highlight the complex nature of using naturalistic, dynamic stimuli of real-world events.

In addition to the odd non-monotonic set-size effect found in the first 3 experiments, a breakdown in lifeguard responses was also noted in the highest set size of Experiments 1 and 2. When the number of swimmers in the pool increases from 6 to 9, the lifeguard responses were noted to diminish. It is odd that the lifeguards' detection should be affected in the higher set size when they are used to supervising much larger numbers of swimmers within their pool zone. One interpretation of this result could be that lifeguards are using a strategy in the low and intermediate set size (3 and 6 swimmers) which is successful, but when used in the higher set size (9 swimmers) it becomes less successful. For example, if a serial search was used, it may be effective with 3 or 6 swimmers, but becomes less useful with 9 swimmers. Response times suggest that lifeguards still respond more quickly than non-lifeguards in this condition, but if they are simply trying to speed up a serial search, they may miss some drownings altogether. This possibility of search affecting drowning detection was also found in Laxton and Crundall (2018), however in their study they found that lifeguards seemed to change search strategy between the intermediate and high set size, and this change appeared to rejuvenate search performance in the higher set size.

If the results of Experiments 1 and 2 are compared to the results of the real drowning trials used in Chapter 4 (Experiments 3, 4 and 5) the diminished performance in set size 9 appears to be better than responses made to drownings in the low set size of all three experiments in Chapter 4. These experiments used real clips which were more representative of the numbers of swimmers a lifeguard would supervise during peak holiday times. The lifeguards in Experiments 1 and 2 detect approximately 90% of drownings in set size 9, whereas lifeguards in Experiments 3, 4, and 5 detected approximately 80% of drowning swimmers in the low set size. Performance in the highest set size (between 60-89 swimmers) was also seen to breakdown in Experiments 3, 4 and 5, which may be a result of the number of swimmers simply being too many, and the scene array becoming too cluttered with swimmers and pool toys to conduct a successful serial search.

7.4.2 Differences between Active and Passive drownings

Experiments 1 and 2 (Chapter 3) found that there were differences between detection of active and passive drownings. Passive drownings were detected faster and more often than active drownings, which goes against what would be expected (salient target pop-out effects; Tresiman & Gelade, 1980; Nothdorft, 2002; Lamy & Zoaris, 2008, unexpected changes in motion; Howard & Holcombe, 2010; Abrams & Christ, 2003). The behaviours of an active drowning, when alone, would be expected to be salient. The failing arms and splashing would expect to draw the viewers' attention and thus would be detected faster within a visual search. In contrast, the passive drowning, when alone, may not be so attention grabbing. The passive drowning, floating face down and still, may need direct attention to spot it. However, when distractor swimmers are also in the search array, this alters the complexity of the visual task, with active drownings sharing similar features to distractors and passive drownings becoming more salient as the behaviour becomes different from the distractors.

Therefore, the faster response times to passive drowning may be a result of the passive drowning being substantially different from the other swimmers in the pool (face down and motionless compared to someone moving across the pool with rhythmic breathing and arm strokes). There is evidence to support this, which shows the effect of target/distractor similarity (Duncan & Humphreys, 1989; Guest & Lamberts, 2011; Feldmann-Wüstefeld & Schubö, 2014; Smith et al., 2006). As previously noted, Alexander and Zelinsky (2012) found when target teddy bears shared 3 out of 4 features with a distractor bears (such as, arms, legs or head) more search errors were made. When the target bear and the distractor bears were similar, more false positive responses were made. This would be expected for distractors that share maximum properties with targets, as features can be easily confused. Fixations for targets were also affected as the similarity between target and distractors increased, with longer verification times for target bears and more distractor bears fixated before the target bear.

The active-drowning targets, in contrast, were responded to less often than the passive targets at set size 3 in Experiments 1 and 2. While the passive drownings may stand out more in the visual search due to the lack of motion, the active drownings may be less salient with certain behaviours of the instinctive drowning response sharing features of the background swimmers (for example, the splash from the failing arms of a drowning swimmer may be similar to the splash from a front crawl or butterfly arm motion, or the submergence and re-emergence of the head being similar to a weaker swimmer's breathing technique). This again fits with the previous literature, which suggests difficulties when target items and distractor items share similar properties (Alexander & Zelinsky, 2012, Neider, Boot & Kramer, 2010; Duncan & Humpreys, 1989). Thus, drownings in the active condition may require more visual integration due to the similarities between active drowning behaviours and the behaviour of other swimmers in the pool. Conversley, the passive drownings may offer enough visual information for a target to be instantly identified. In the eye-movement data of Experiment 1, the active drowning swimmers, overall, received longer average fixation times compared with passive drowning swimmers, supporting this interpretation. Active drowning swimmers were fixated for longer before participants made a manual response.

It may also be possible that the faster responses to the passive drownings are driven by the sudden change in motion of the drowning swimmer, particularly when in comparison to the movement of the distractor swimmers. Therefore, the lack of movement in the passive drowning stands out more than the change in movement of the active drowning swimmers when compared to the distractor swimmers. There is research that has suggested that search for a certain type of target (type A) among distractor items of a different type (type B) is easier than when the search is the other way around (target type B among distractor items A) (Treisman & Souther, 1985). In dynamic stimulus sets, Ivry and Cohan (1992) have found that search for a fast moving target in slow moving distractors is more efficient than searches for slow moving targets in an array of fast moving distractors.

However, this finding of faster responses to passive drowning targets in an array of moving distractors differs from typical search-asymmetry research. Previous literature on attention capture has found that searches for stationary targets in moving distractors and backgrounds are harder, with response times for target detection being slower than detection of moving target in stationary distractors (Verghese & Pelli, 1992; Royden, Wolfe & Kempin, 2001). Research has also demonstrated that more motion is associated with attention capture and that unexpected changes in motion draw attention, which subsequently alters the outcome of the search (Howard & Holcome, 2010). It is interesting that in this applied context, the passive drownings, which are characterised by less motion, are getting better performance generally. This is potentially due to the meaning and context of the real-world swimming pool scenes, and shows the importance of real-world factors. This current research has demonstrated that in a real-world context the behaviours of targets and distractors change the outcome of the search. For instance, the lack of motion in the passive drowning swimmer captures attention because the behaviour is so different from the distractor activity. Whereas, the changes in active drowning are more difficult to spot with the similarities between the *instinctive drowning response* and normal swimming behaviours, and these changes are in the behaviour of swimmers rather than to the speed or motion direction of the drowning event.

Despite this possibility, the experiments in Chapter 4, which explored drowning detection with only active drowning targets in real environments (highly busy pools with children playing and using real drowning footage), further demonstrate the importance of target/distractor similarity. In these trials there was greater overlap between the drowning swimmer's behaviour and the other swimmers in the pool (e.g. the *instinctive drowning response* being visually similar to other swimmers' play behaviours of splashing and disappearing under the water). The greater similarity between the drowning swimmer and the fun swimming behaviours of the other people in the real pool clips used in the stimuli of Experiments 3, 4, and 5 appeared to cause greater issues for accurate drowning detection for the non-lifeguards, particularly in the highest set size (when there are between approximately 60-89 swimmers in the pool).

The undefined nature of the drowning event also potentially affected the detection rates of the non-lifeguard participants in these real drowning clips (e.g. uncertainty of drowning behaviours or inaccurate representations of drowning based on TV and film). Similar difficulties with searches that have a level of uncertainty around the target are noted in previous research, with errors in target detection (Hout & Goldinger, 2015; Schmidt & Zelinsky, 2009). The limited experience of non-lifeguards with drownings possibly accentuates the uncertainty of what the target looks like, resulting in the lower drowning detection noted in Chapter 4.

7.4 Theoretical Implications

7.4.1 Experiential effects in dynamic visual search tasks

One of the main findings of this thesis, which has consistently appeared throughout, is the greater performance of the lifeguards in their responses to drowning swimmers. In chapters 3 and 4, lifeguards were found to have consistently faster response times to drowning swimmers, and also the lifeguard responses tended to be more accurate than the non-lifeguards. Lifeguard superiority on both of these measures fits with previous studies that have demonstrated expert superiority in detecting targets in static image searches (Biggs & Mitroff, 2014, Nodine et al., 2002; Sheridan & Reingold, 2014), and for detecting events in complex dynamic environments (Faubert, 2013; Howard et al, 2010; Howard et al., 2013).

Although a consistent effect of lifeguard superiority was found in these experiments for participants' behavioural responses, it was not possible to distinguish what was driving this superiority effect in these experiments. While lifeguards demonstrated greater behavioural responses in the drowning detection tasks, the eye-movement measures between lifeguard and non-lifeguard participants failed to find any significant differences in Experiments 1 and 4. Similar results to these, with no difference between eye-movements in novice and experienced lifeguards, were found in Page et al. (2011), who made the suggestion that the lack of difference was due to experienced lifeguards relying on contextual knowledge to drive search, rather than employing a particular search strategy. In the current thesis, both participant groups, in Experiments 1 and 4, appear to scan the scene similarly, fixating a similar number of drowning swimmers, in roughly the same amount of time. This lack of difference between the two participant groups' eye-movements suggests lifeguard superiority on these visual search tasks is not actually driven by a superior scanning strategy (i.e. knowing where, when or how to look around the pool). Instead, the drowning detection advantages seen in lifeguard responses appear to be the result of a better ability to recognise the behaviours of a swimmer in distress.

7.4.2 Visual processing and drowning recognition

The results of Experiments 6 (Chapter 5) presented the first investigation into the processes that may drive the superior drowning detection in lifeguard visual search when compared to non-lifeguards. This experiment explored both lifeguards' and non-lifeguards' performance on two short cognitive tasks, and the association between performances on these tasks with performance on a short drowning-detection task. The two cognitive tasks employed to assess whether there are any contributing cognitive skills in lifeguard drowning detection were a FFOV task and a MOA task. Results showed that lifeguards were better at both of the tasks employed. However, only performance of the central task of the FFOV was significantly associated with drowning detection for the lifeguards. This supports the suggestion that one of the contributing factors to superior lifeguard visual search is the ability to recognise and process the characteristics associated with drowning swimmers.

This finding of processing advantages at the point of fixation fits with other areas of research that has found similar results in real-world applications. For instance, there are a number of studies that have found better processing of search items in participants that are considered domain experts, such as sports players or video game players (Faubert, 2013; Bialystok, 2006; Castel, Pratt & Drummond, 2005). One example of this comes from tennis (Paul et al., 2011), with results suggesting that the faster processing of expert tennis players in identifying the flight path of a ball, provides them with an advantage in planning the appropriate motor response.

This possibility was explored in Experiment 7 (Chapter 6), which employed a perceptual processing task that required participants to identify drowning targets from short-bursts of isolated swimming videos. This training was explored with non-lifeguard participants and found drowning detection could be improved on a post-intervention drowning-detection test, with pre-intervention drowning detection used as a covariate. Non-lifeguard participants who completed an active-control task were not found to make any significant improvement in their drowning detection on the post training-intervention task. The idea of using perceptual tasks to train search skills in complex real-world tasks has been well documented, with results demonstrating an improvement in processing of search items (Clark et al., 2015; Lev et al., 2014; Owsley, 2013). In one real world example, Crundall, Howard and Young (2017) found similar results in terms of perceptual processing training in driving research. When training car drivers to spot motorcycles at road T-junctions, Crundall et al. (2017) employed a Pelmenism game, which required participants to distinguish between different motorcycles whilst matching them into pairs. It was believed that the exposure to the motorcycles and the level of engagement with the training material improved subsequent detection of on-coming motorcycles at T-junctions after the training. Performance of a control group, who matched picture pairs of fruit, did not improve post-intervention performance on the T-junction test. The exposure to domain-specific stimuli may produce improve processing of target items in searches of visual scenes. Taking this into account, if the processing of the drowning swimmer is improved through the perceptual training task used in Experiment 7, participants' detection of drowning swimmers in a pool setting should improve, regardless of the scanning strategy employed.

Within the idea of processing drowning characteristics, it is also interesting to note that the verbal instructions given regarding the different behavioural features of the drowning types before completion of Experiment 2 did not affect the drowning-detection performance of the participant groups. Past research has found that verbal description of target templates have been used to enhance search performance, with searchers being able to distinguish between target and distractor items in a similar way to participants using a picture template (Malcolm & Henderson, 2010; Maxfield et al., 2014; Vickery, King & Jiang, 2005). While the verbal information given in Experiment 2 did not appear to have an effect on drowning detection, the visual exposure to drowning swimmers, either through experience (lifeguards and lifesavers), or through the training tool employed in Experiment 7, does appear to significantly improve responses in the drowning-detection task. It could be that the verbal information given on drowning characteristics is clouded by participants' existing perception of drowning (from movies or television) and thus they fail to recognise and process the subtle drowning behaviours of the *instinctive drowning response.* Pre-established mental representations that the lifeguards have of the general drowning characteristics of the *instinctive drowning response* may be driving task performance through processing of behaviours rather than superior scanning or knowing what will be in the search. This interpretation is also supported by the lack of difference in the response accuracy to drowning swimmers between lifeguards and lifesavers (who are not trained to scan for drowning, but rather what a drowning swimmer looks like, and how to then intervene).

It might also be possible to use knowledge elicitation tools (e.g. card sorting, reparatory grids) with expert lifeguards, to identify better descriptions of drowning behaviours. These tools are argued to provide verbal descriptions of behaviours that might have previously been considered procedural, leading to better descriptions on what cues to look for. In one real-world example, Okechukwu Okoli, Weller and Watt (2014) used a knowledge elicitation tool to explore expert firefighters' tacit knowledge. The firefighters were asked to recall remarkable and memorable major incidents which challenged their expertise, and then asked to go over the incident a second time to identify key decision points. The results revealed important salient cues that firefighters use at critical decision points. These included safety related cues, such as cracked walls or roof stability, or environmental cues, such as wind direction and velocity. Okechukwu

Okoli et al. also suggested that knowledge elicitation could be used to transfer such tacit knowledge to novices, but it is only useful if novices are given the opportunity to learn the relevant cues. For lifeguards, these knowledge elicitation tools could perhaps produce a better description of drowning behaviours that could allow declarative approaches to training (i.e. with better descriptions, telling people what to look for might actually help). The more direct alternative, which was used in this thesis, is to just show people examples of these drowning behaviours and this supports previous research that has suggested cue discrimination is regarded as one of the hallmarks for expertise (Gobet, 2005; Perry & Wiggins, 2008).

7.5 Applied Implications

In addition to the theoretical implications discussed above, we should also consider the applied implications of the research presented in this thesis, such as the applications of this research for the process of testing and training lifeguards within industry settings. These applied implications will be discussed below.

7.5.1 Testing and training lifeguard superior search

One of the clear effects found in this thesis is the superiority of lifeguards drowning detection in both accuracy and response times to drowning incidents. This finding replicates that of Laxton and Crundall (2018), who used a similar methodology for testing lifeguard drowning responses and the same dynamic stimuli from this experiment was used in Experiments 1 and 2 (Chapter 3) of this thesis. This consistent experiential effect is also in line with previous research, which has explored experiential superiority in real world, dynamic visual search tasks (Howard et al., 2013; Crundall & Eyre-Jackson, 2015; Page et al., 2011). The clear effect for lifeguards' superior performance demonstrates that this research could potentially be used for a selection process for new lifeguards, discriminating between people who have the necessary skills for successful drowning detection from those who may need further training to develop drowning detection. This assessment would need to follow immediate training, as it is unlikely that anyone would have a natural ability to detect drowning swimmers. It could be possible to use it as a tool to remove those who have not demonstrated learning benefits, or identify those who need further training in the detection of drowning incidents.

The aim of Experiment 7 was to develop a potential tool for training drowning detection. Participants had to discriminate between short-isolated videos of either swimmers or drowning incidents. The results demonstrated improved responses of the participants who received the drowning detection training, suggesting advantages of using a drowning exposure task to improve drowning detection skills. For example, during the lifeguard training course, lifeguards could use the tool to increase their knowledge of potential drowning characteristics. Extremely short exposures to the training tool appear to have positive results. If one assumes that the training effect found in Experiment 7 persists over time (see section 7.6 for a discussion about this), then this tool could easily be deployed within a lifeguard-training course. The training part of the experiment ran 3 seven-minute blocks and therefore could be easily completed during a standard training course or as online-homework for the trainees. This training could be used alongside the drowning detection test, incorporating an element into the lifeguarding qualification that focuses of drowning detection surveillance.

One of the interesting points of the drowning stimuli used in this thesis is the applications to the real world. The use of naturalistic and dynamic footage of swimmers in distress or drowning allows for comparisons to lifeguarding in the real world. The stimuli used throughout this thesis have differed from traditional laboratory-based visual search tasks, in that observers are normally required to search static images, artificial stimuli or scenes where the target item is always present (Biggs et al., 2013; Biggs & Mitroff, 2014; Henderson et al., 2009; Hess et al., 2016; Page et al., 2011; Visalli & Vallesi, 2018). Instead, the dynamic stimuli used throughout the thesis were complex, with real footage of swimming pools with scenes where drownings develop over time (in both simulated and real drowning clips), and are not present from the start of the trial. The use of real swimming and drowning footage means that results are comparable to the real-world search of lifeguards in that complex dynamic environment, particularly in the video clips with high numbers of swimmers in the pool. This means that the drowning detection test used throughout the thesis and drowning training used to improve the visual search of non-lifeguards in Experiment 7 could be implemented in actual lifeguard training. This could be as a measure of testing and training drowning detection before a lifeguard is in a position to supervise a pool of swimmers or as a tool to expose lifeguards to drowning incidents, decreasing their thresholds for events that are rare occurrences in pools.

7.6 Limitations of the research and future directions

Throughout this thesis, the general conclusions have shown lifeguard superiority in drowning detection. However, the studies are not without their limitations. First, we must consider the use of videoed stimuli and its applications to the real world. Although this thesis has shown that lifeguards have superior visual search for detecting a drowning swimmers in a series of visual search tasks, they have solely focused on drowning detection. The stimuli used in this thesis are also presented in a series of 30-second video clips. While this has allowed for the testing of drowning detection in experts and for contributing cognitive skills to be assessed, it is not fully representative of the lifeguarding experience. Lifeguards face long hours of inactivity when supervising pools. Going forward, one interesting research avenue would be to take an approach that explores how lifeguards engage with scenes over a longer period and how continual surveillance is affected over time. For example, are swimmers that have been identified as at-risk re-fixated numerous times? Do some swimmers receive longer fixation durations? Does vigilance decrease over time, with longer single fixations and fewer eye-movements?

The current video stimuli were also limited in terms of a fixed camera view (rather than having the opportunity to move around the pool), visual resolution of the footage, and the limited viewing angle bounded by the border of the monitor on which it is presented. In addition, there may be issues with the lifeguard's ability to engage with swimmers when using videoed stimuli. Whilst the study enables for the lifeguards' search skills to be tested, in a real swimming pool the lifeguard would be able, to a certain extent, to move around the poolside to get a better angle to see some swimmers that are possibly obscured or move further towards the deep or shallow end to see things in the pool better. Also, in training, lifeguards are also taught methods of hazard prevention to help stop some drowning and distress events occurring. There are three stages of hazard prevention that are taught, these being: early intervention, non-critical intervention, and critical intervention. In early intervention a lifeguard stops an unwanted behaviour as it is starting (e.g. asking a hesitant swimmer to stay in shallower water). Non-critical intervention refers to those times when a lifeguard intervenes when an individual is engaging in dangerous behaviour, even though they are not in danger at that point (e.g. a non-swimmer moving out of their depth). Critical interventions occur when an incident has happened (e.g. a non-swimmer has gotten into deep water and is drowning; Blackwell, 2016). This is similar to the hazard perception framework that has been applied to driving. This framework recognises potential hazards, which may lead on to developing hazards; finally resulting in fully-materialised hazards (Crundall, 2016; Pradhan & Crundall, 2017). With this, lifeguards would be encouraged to interact with swimmers, for example, asking if a swimmer is ok. It should also be acknowledged that previous research has demonstrated that eye-tracking in real-world environments elicits different behaviours from laboratory studies using videoed-footage of real-world scenes (Foulsham, Walker & Kingstone, 2011; Kingstone, Smilek & Eastwood, 2008). However, in regard to lifeguarding, it would be particularly difficult to explore drowning detection in real-world environments, with drowning and distress incidents being an incredibly rare occurrence for most lifeguards.

To overcome these problems in future research, it may be possible to use virtual reality, creating either 360^{o} videos of pools or an animated environment, which mirrors that of real pools. This would overcome problems with the videos in terms of the fixed camera position and videos being bounded by the edges of a monitor. This method would also expose new lifeguards to close-to-real swimming pool environment, which could build up exposure to drowning behaviours, but also provide a catalogue of knowledge for drowning events. Despite limitation with the current stimuli, the studies still provide insights into drowning detection, the cognitive skills that might contribute to lifeguard surveillance for drowning swimmers and training methods for improving drowning detection.

One further important limitation to note is that only two cognitive tasks were selected to assess skills that may contribute to lifeguard visual search. It was thought that both MOA and FFOV were related to aspects of lifeguard surveillance; however, other unaccounted cognitive skills may also influence searches for drowning detection. For example, performance on embedded-figures tasks (Smith & Broadbent, 1980; de-Wit et al., 2017) may show how lifeguards potentially see through clutter. Similarly, performance in mental rotation tasks (Shepard & Metzler, 1971; Feng et al., 2017) may show how lifeguards understand activities of swimmers from different perspectives (some activities may look dangerous from one angle, but not so dangerous if seen from different view). Lifeguards may have also developed their working memory for items in the pool (better short-term memory for people in the pool and any changes in swimming behaviours).

The study of these underlying cognitive mechanisms addresses a fundamental debate: can domain-specific skill be predicted by domain-free cognitive aptitudes. While the current research did not find evidence for this, additional cognitive skills could potentially be explored in future research, investigating whether individuals who possess higher abilities in these cognitive skills would make better lifeguards in terms of their drowning detection abilities.

It may also be possible that the MOA task was not the most suitable for the context-free cognitive tasks. Lifeguards are exposed to multiple moving objects on a daily basis (tracking swimmers in a pool), which may be more relatable to the MOT task. Therefore, an association may have been found between MOT and drowning detection if a MOT task had been used instead. However, in previous research the MOA task has been found to elicit more eye-movements from participants compared to standard MOT tasks (where observers can passively watch the movement of target items) (Mackenzie & Harris, 2017). The eye-movements elicited during MOA tasks potentially mimic the movements of the lifeguard while observing the pool, with swimmers moving in and out of the observers' focus, an important factor, which may not be accounted for in MOT tasks that usually require participants to track items from single fixation point.

It is also important to note the limitations to the training explored in Chapter 6 (Experiment 7). First, due to time constraints participants were not followed up in order to assess the longevity of the training benefit. It would be interesting to see if the participants training in drowning behaivours are still better than control participants three months later. If follow-up research did not show the longevity of the intervention, it could be possible in future research to explore if longer or more frequent training helps the effects of the training tool to last longer. Second, the training stimuli are taken from the same pool that we have used for the post-intervention test stimuli. This only really measures near-transference of training rather than far-transference (Barnett & Ceci, 2002; Sala et al. 2019; Zelinsky, 2009). Will training on children with rubber rings in this one pool transfer to spotting drowning characteristics of adult drowners in other pools? If not, a much wider and varied selection of drownings might be needed as training stimuli.

One final direction for future research would be to consider how lifeguards' superior drowning detection is affected by psychological phenomena such as low-target prevalence (Wolfe, 2006; Wolfe et al., 2005) or how vigilance is affected in low-stimulation environments (Casner & Schooler, 2015; Griffiths & Griffiths, 2013). The current studies had an artificially high number of drowning incidents that may have lowered thresholds and increased participant motivation. This was necessary to ensure that sufficient trials were presented within a testing session to achieve a stable measure of performance. Future studies may however reduce the occurrence of drowning incidents to mimic the extremely rare target effect noted by Wolfe et al. (2005).

Motivational differences between the two groups could also have led to inflated performance for the expert group. This could be from lifeguards wanting to perform well or competition with colleagues. It is also possible that that location differences in testing may have created different priming effects between lifeguard and non-lifeguard participants. Theory on context dependant memory suggests that there is an improvement in recall of information when the context is the same for encoding and retrieval (Godden & Baddeley, 1975). There is also a suggestion that an attentional set during visual search can be influenced by memory for the context in which a task is performed (Cosan & Vecera, 2013). Therefore, search outcomes could have been influenced by some participants being tested in a poolside location. However, one of the key results of the thesis was the improvement of the non-lifeguard participants' drowning detection after completing the intense classification task. Both participant groups in this training experiment were tested in the same laboratory conditions.

7.7 Original contribution of the current research

Despite there being substantial literature based on both theoretical and applied visual search, there have been a limited number of studies exploring the visual search skills of lifeguards. In addition, there have been few applied visual search studies that explore the effects of dynamic scenes that are both naturalistic and complex. The research of this thesis has begun to explore lifeguard visual search skills, developing the findings of earlier research (Laxton & Crundall, 2018) and adding to the limited number of studies on lifeguard experience in drowning detection (Page et al., 2011; Lanagan-Leitzel et al., 2015). Existing research into lifeguard visual search has been limited in understanding the complexities of drowning detection. For example, low-fidelity stimuli in tightly controlled conditions have previously been employed (Page et al., 2011). To address this issue, the current thesis explored lifeguard visual search in naturalistic and dynamic scenes, which demonstrated lifeguards detected more drowning events (Experiments 1-5), but there were no difference in eye-movements (Experiments 1 and 4). In addition to extending existing literature on lifeguard drowning detection, the research in this thesis is the first of its kind to explore cognitive skills that may contribute to lifeguarding visual search in detection of drowning swimmers (Experiment 6). The only element of performance that contributed to drowning-detection performance was performance on the central task of the FFOV, which was actually the only domain-specific element of the tasks. The results do not support the notion of 'naturally-gifted' lifeguards, though it is acknowledged that other tests (e.g. embedded figures, mental rotation, etc.) may produce different results. Finally, from the exploration of the cognitive skills, this thesis has been able to explore how drowning detection can be trained (Experiment 7). This training method has implications to the real-world and could potentially be used to make recommendations to current training methods and practice for lifeguarding qualifications. Additionally, the real drowning stimuli used in Experiments 3, 4 and 5 could also be implemented as a testing tool for either new lifeguards, in order to attain whether their drowning detection is to a certain standard, or as a tool to highlight any training needs in experienced lifeguards.

7.8 Thesis conclusion

The central aim of this thesis was to examine whether there are any experiential effects in lifeguard's surveillance of swimming pools when searching for drowning detection and how this drowning detection can be trained in the future. The research carried out here has demonstrated that there are experience effects in lifeguard visual search in a naturalistic and dynamic visual search task of swimming pool footage. This was shown in both simulated drowning footage and real drowning footage. This has extended previous findings of lifeguard superiority in visual searches of simulated drownings. Importantly, it has also demonstrated that performance in a drowning-detection visual search task appears to be primarily reliant upon the processing of drowning characteristics once foveated, rather than knowing where, when or how to search a pool scene. Additionally, it has been found that drowning detection can be trained in individuals who have no experience with lifeguarding or drowning behaviours through a perceptual training tool, which increases exposure to drowning characteristics in a controlled manner, gradually increasing the level of background that trainees must cope with. These results could be used to inform future training methods for lifeguard qualifications, creating useful tools for training and assessing lifeguard drowning detection.

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