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Lifeguard training sharpens brain dynamics in novices during drowning detection

Marie-Stephanie Cahart [a,*], Marcus S. Smith [b], Benjamin T. Sharpe [c], Steven C.R. Williams [a], Simon Hill [a], Jo Talbot [d], Nick Grazier [d], David J. Lythgoe [a], Jenny Smith [b]

[a] Neuroimaging Department, Institute of Psychiatry, Psychology and Neuroscience, Kings College London, 16 De Crespigny Park, London SE5 8AB, UK
[b] Institute of Applied Sciences, University of Chichester, West Sussex PO19 6PE, UK
[c] Institute of Psychology, Business and Human Sciences, University of Chichester, West Sussex PO19 6PE, UK
[d] Royal Life Saving Society UK, Redhill House, 227 London Rd, Worcester WR5 2JG, UK

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ABSTRACT

Drowning is a critical global health issue, responsible for over 236,000 deaths annually. Lifeguards play a key role in preventing drowning incidents by continually monitoring bathers and detecting hazards taking place in highly dynamic environments such as pools. Previous studies have observed that specialized drowning detection training is closely associated with enhanced detection of drowning events. However, the neural mechanisms underlying this greater drowning detection performance remain unclear. Here, we address this gap in the literature by comparing brain function between lifeguards and novices, and examining changes in brain dynamics associated with drowning detection training. Using a dynamic functional connectivity analysis method called Leading Eigenvector Dynamics Analysis (LEiDA), we analysed time-varying patterns of brain activity in 18 lifeguards and 16 novices during a drowning detection task and at rest. Our findings revealed significant differences within group and between groups in the probability of occurrence of attention-related brain networks, particularly the frontoparietal, ventral attention and Default Mode networks. These findings provide novel insights into the neural basis of lifeguard expertise and how specialized training shapes neural mechanisms and improves drowning detection performance in critical lifesaving scenarios.

1. Introduction

Lifeguards play a pivotal role in preventing drowning events by continuously monitoring swimmers and anticipating potential hazards in highly dynamic aquatic environments (Lanagan-Leitzel et al., 2015). The task of lifeguard surveillance presents unique challenges, requiring the ability to sustain attention over extended periods and accurately detect rare events amidst a continuous stream of visual information across large bodies of water (Lanagan-Leitzel et al., 2015; Schwebel et al., 2011). Sustained attention, defined as the continuous focus on a specific task over an extended period, is considered a key executive function underlying drowning detection performance (Sharpe et al., 2024). Previous research has demonstrated that sustained attention significantly contributes to performance on measures of working memory capacity (Unsworth & Robison, 2016). Moreover, lifeguards with greater working memory capacity have been reported to display enhanced detection of drowning events during simulated tasks (Sharpe et al., 2024). However, the neural mechanisms underpinning this improved ability to accurately detect drowning events remain poorly understood.

Neuroscientific research suggests that attention is sustained through the coordinated activity of multiple brain regions (Bressler & Menon, 2010; Seeburger et al., 2024). Yeo et al. (2011) identified four major brain networks involved in attentional control. Enhanced sustained attention has typically been associated with increased task performance and activation of the frontoparietal and dorsal attention networks (Pamplona et al., 2020). These networks, collectively known as the task positive network, are involved in top-down, task-oriented attention and effortful cognitive control (Petersen & Posner, 2012). In contrast, the Default Mode Network (DMN) has been found to deactivate during attention-demanding tasks (Pamplona et al., 2020; Raichle et al., 2001) and is associated with internal cognitive processing such as introspection and mind wandering (Mason et al., 2007). Additionally, the ventral attention network, involved in monitoring salient outputs and playing a

* Corresponding author.
E-mail address: marie-stephanie.cahart@kcl.ac.uk (M.-S. Cahart).

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key role in alerting, has been linked to task performance and attentional control (Seeburger et al., 2024).

The present study employed a two-part experimental design to investigate the neural correlates of drowning detection performance. Study 1 compared brain function between lifeguards and a novice control group (i.e., non-lifeguards). Study 2 explored changes in brain dynamics associated with drowning detection training within the control group. Indeed, previous studies have shown that lifeguard-specific drowning detection training not only enhances performance in drowning detection tasks (i.e., number of correctly identified drowning events) but also outperforms standard working memory training in terms of performance improvement (Sharpe et al., 2025). However, the brain mechanisms underlying this increased drowning detection performance after training remain unclear.

Given that sustained attention is known to fluctuate over time (Seeburger et al., 2024; Sharpe & Tyndall, 2025), we have chosen to study the time-varying patterns of brain activity using Leading Eigenvector Dynamics Analysis (LEiDA), a computational neuroimaging technique which examines changes in brain functional connectivity over time (Cabral et al., 2017). LEiDA works by analysing the dominant patterns of brain connectivity at each moment in time, allowing researchers to identify recurring "brain states" that the brain transitions between during scanning. LEiDA characterizes states, or networks of brain regions, that alternate in activation over the entire duration of the scan. Each timepoint is associated with a state, or network, that dominates at that specific moment. This technique allows for the extraction of the probability of occurrence of each state, defined as the percentage of timepoints during which the state dominates during the scan. LEiDA has been successfully employed in studies using both resting-state and task functional Magnetic Resonance Imaging (fMRI), shedding light on the dynamics of various cognitive processes including attention (Cahart et al., 2024; Cahart et al., under review), alertness (Magalhães et al., 2021), trait self-reflectiveness (Larabi et al., 2020), and action-perception (Heggli et al., 2020). To obtain a more comprehensive understanding of brain function differences between groups and within group, we have chosen to investigate brain dynamics both during a drowning detection task and at rest.

In Study 1, it was hypothesized that lifeguards would demonstrate significantly superior drowning detection performance at baseline compared to control participants, as measured by the number of correctly identified drowning events. Additionally, the study anticipated that lifeguards would exhibit distinct brain dynamics, specifically in the probability of occurrence of states associated with the frontoparietal, dorsal attention, ventral attention, and default-mode networks, compared to controls. These differences were expected to manifest both during the active drowning detection task and during resting-state brain activity.

For Study 2, the hypotheses focused on within-group effects of training among the control participants. It was expected that drowning detection performance would significantly improve in this group following the training intervention, relative to their pre-training performance. Furthermore, changes were anticipated in the brain dynamics of the same four attention-related networks, frontoparietal, dorsal attention, ventral attention, and default-mode, after training. These neural differences were hypothesized to be evident both during the drowning detection task and at rest.

2. Materials and methods

2.1. Participants

Eighteen lifeguards and 18 non-lifeguard controls initially took part in the study after providing written informed consent (ethics number HR/DP-22/23–33492; King's College London Research Ethics Committee). All participants were males, right-handed, with no history of psychiatric disorder or neurological disease, and met MRI safety criteria (i.e., no pacemaker, no metal in the body, no claustrophobia). Males were chosen in order to limit gender-differences typically observed in brain anatomy (Giedd et al., 2012). Lifeguards had an average of 3.96 years of experience and were all certified by and recruited through the Royal Life Saving Society (RLSS) UK. Importantly, all lifeguards had received standardized RLSS training in drowning detection and water rescue techniques as part of their certification process. Controls were recruited through social media and King's College London's research recruitment mails. Of the 18 controls, two were excluded because of one missing their second scan and the other one falling asleep during the task. The final number of participants included in the analyses consisted of 18 lifeguards (aged = 22.6 ± 3.7 years) and 16 age-matched controls (aged = 22.3 ± 3.2 years). Power calculations were conducted using G*Power 3.1.9.7, assuming a medium effect size (Cohen's d = 0.8) with $\alpha = 0.05$ and power = 0.80. This indicated a minimum sample size of 16 participants per group for between-group comparisons and 15 participants for within-group comparisons, which our final sample met.

2.2. Procedure

All 34 participants underwent MRI scanning sessions at the Centre for Neuroimaging Sciences (Institute of Psychiatry, Psychology and Neuroscience; King's College London). Each lifeguard attended only one scanning session, while each control attended two scanning sessions, once before and once after online drowning detection training. The time interval between the two scanning sessions for controls was 5–6 weeks (mean = 5.3 ± 0.4 weeks). Each session consisted in filling in questionnaires and undergoing a 75-minute MRI scan.

2.3. Questionnaires

Upon their first scanning session, all participants filled in the Cognitive Failures Questionnaire (Broadbent et al., 1982) before going into the MRI scanner. The Cognitive Failures Questionnaire consists of 25 items measuring forgetfulness, distractibility and false triggering in everyday life. The aim was to eliminate differences in cognitive processes between groups at baseline. The questionnaire has been shown to achieve high internal consistency reliability ($\alpha = 0.92$) (Bridger et al., 2013).

After each scan, all participants filled in the NASA Task Load Index (NASA TLX) questionnaire (Hart & Staveland, 1988), which measures perceived workload across six distinct dimensions such as mental demand (i.e., how mentally demanding the task was), physical demand (i.e., how physically demanding the task was), temporal demand (i.e., how hurried or rushed the pace of the task was), performance (i.e., how successful the participants *felt*, or *perceived,* they were in accomplishing the task), effort (i.e., how hard it was to perform this task), and frustration (i.e., how insecure, discouraged, irritated, stressed or annoyed they felt). Participants were required to rate each item on a scale from 0 to 21. The scales have shown strong internal consistency reliability (α) in previous studies (0.72) (Hoonakker et al., 2011).

2.4. MRI data acquisition

All participants were scanned in a 3 T MR scanner (Signa Premier, General Electric, Chicago, IL, USA). On each visit, they underwent an anatomical T1-weighted MPRAGE scan with the following parameters: repetition time = 2658 ms; inversion time = 860 ms; recovery time = 1015 ms; echo time = 2.952 ms; flip angle = 8°; field of view = 256 mm^2; matrix size = 256 × 256; 208 slices, with slice thickness = 1 mm. After the anatomical scan, the participants underwent a resting-state sequence: multiband factor 4, no in-plane acceleration: repetition time = 933 ms; echo time = 32 ms; flip angle = 60°; field of view = 221 mm^2; matrix size = 82x82; slice thickness = 2.7 mm; total acquisition time = 9 min. The other functional run, which immediately followed the resting-state sequence, was dedicated to the drowning detection task and had the following parameters: multiband factor 4, no in-plane acceleration: repetition time = 1000 ms; echo time = 32 ms; flip angle = 60°; field of view = 221 mm^2; matrix size = 82x82; slice thickness = 2.7 mm; total acquisition time = 30 min. During the acquisition of the resting-state sequence, the participants were asked to stare at a white cross on a black screen in a wakeful resting state and were provided with headphones and earplugs to limit background noise generated by the MRI machine. During the acquisition of the other functional run, the participants were required to carry out the drowning detection task.

2.5. *Drowning detection task*

The drowning detection task was adapted from the lifeguard-specific Bobbing Along drowning detection tool used in previous studies (Sharpe et al., 2023; 2024; Sharpe & Smith, 2024). The task was developed using Unreal Engine 4 (UE4), with custom C++ code implemented to provide the necessary functionality for a standard paradigm task. Furthermore, built-in blueprints were used to optimize the creation and management of the 3D environment (Hill, 2021). The video consisted in a simulation of 48 bathers swimming across 64 navigation boxes in a randomized manner (Fig. 1). The full task is available upon request from the corresponding author. The entire task featured 12 drowning events, taking place at irregular intervals throughout the task (Table 1), each occurring in one of the 64 navigation boxes (Table 2). The timing of drowning events was pseudo-randomized to avoid predictable patterns while maintaining ecological validity. Forty-eight bathers were included in the task to align with the highest count used in prior research (Sharpe et al., 2024). Additionally, 12 drowning events were chosen to ensure enough statistical power given the 30-minute fMRI task length, while also considering ecological validity, as more than 12 events would have been unrealistically frequent compared to real-life scenarios.

Ecological Validity Considerations: The drowning detection task was designed to replicate key aspects of real-world lifeguarding scenarios while maintaining experimental control necessary for neuroimaging. The simulation incorporated several ecologically valid features: (1) multiple bathers moving simultaneously in unpredictable patterns, mimicking crowded pool conditions; (2) passive drowning events following the Instinctive Drowning Response characteristics observed in real drowning incidents; (3) the requirement for sustained vigilance over extended periods; and (4) the visual search demands typical of lifeguard surveillance. However, we acknowledge that certain real-world factors such as environmental distractions, varying lighting conditions, and three-dimensional water movement could not be replicated in the controlled laboratory setting.

All participants were presented with the exact same task, with drowning events taking place in the same order. Each event lasted 30 s, with the bather gradually disappearing under water until full submersion, mimicking the description of passive drowning in line with the Instinctive Drowning Response (Pia, 1974). Ten seconds after submerging entirely, the bather re-emerged and resumed their randomized swimming pattern. The re-emergence of bathers was included to maintain the continuous nature of the surveillance task and prevent participants from simply counting disappeared bathers, thus requiring genuine detection of the drowning process rather than absence of swimmers.

Participants were required to respond to each drowning event using a button box. They were asked to press the button as soon as they identified a drowning incident taking place. If the button was pressed within the 30-second window, then the response was 'correct'. All participants got a 'correct' score between 0 and 12. In the event of the button being pressed outside of this window, the response was classed as a 'false positive', as it meant that the participant identified a drowning event that was not actually taking place.

2.6. *Drowning detection training*

Between both scanning sessions, all controls took part in online drowning detection training adapted from a previous study (Sharpe et al., 2025). The training consisted of watching one 30-minute video

Table 1
Table featuring the time each of the 12 drowning events was set to start and end, in minutes.

Drowning event	Time drowning starts (in mins)	Time drowning ends (in mins)
1	1:15	1:45
2	3:45	4:15
3	4:55	5:25
4	7:15	7:45
5	9:30	10:00
6	12:45	13:15
7	15:15	15:45
8	16:25	16:55
9	19:15	19:45
10	23:45	24:15
11	26:15	26:45
12	28:30	29:00

Table 2
Mapping of the 64 navigation boxes, with numbers indicating the location and order of each of the 12 drowning events.

1,11					8		3
9			5			6	10
4		7					2,12

Fig. 1. Screen capture of the Bobbing Along task with 48 bathers.

online, once each week, over 4 weeks, to balance training benefits with ethical considerations such as limiting participant burden. This approach has previously successfully improved drowning detection (Sharpe et al., 2025). The link to each video was sent to each participant at the beginning of the week they were due to watch it. The order of the training videos was randomized. Each video was made up of 6 clips that each involved one simulated drowning scenario similar to those presented in the Bobbing Along task. At the end of each clip, the footage of the specific drowning event was replayed and the drowning location was highlighted with a red arrow pointing downwards to show the specific location where the drowning incident took place. We chose to include only 6 drowning events to maintain ecological validity, as replays after each event to highlight event location would have made 12 events too frequent for a 30-minute video. In line with prior work (Sharpe et al., 2025), the total number of bathers in each clip was 16 in order to keep the training videos at a manageable level of difficulty. The aim was to ensure that the drowning events were clearly illustrated so participants could effectively learn to recognize similar situations in the future. Compliance was ensured by requiring all controls to either add their initials to the comments below the video upon watching the video or confirm via email that they had watched the training video. The next video was sent out only after confirmation had been received.

2.7. MRI data pre-processing

Functional Magnetic Resonance Imaging (fMRI) data preprocessing was conducted to prepare the neuroimaging data for subsequent connectivity analyses. Statistical Parametric Mapping (SPM12; Wellcome Trust Centre for Neuroimaging, London, UK) and the CONN toolbox Version 21a (Whitfield-Gabrieli & Nieto-Castanon, 2012) were used to preprocess the data. The functional data were realigned, registered to structural images, spatially normalized into the Montreal Neurological Institute (MNI) standardized space and smoothed with a Gaussian filter with a full width at half maximum of 5.0 mm. As part of the CONN toolbox's pipeline, the artifact rejection tool (ART) (https://www.nitrc.org/projects/artifact_detect) was also run for outlier detection. For each volume identified as an outlier, a covariate was included as part of the denoising regression step to reduce the impact of those scans on the subsequent connectivity analyses. Furthermore, the anatomical CompCor method (component-based noise correction method; Behzadi et al., 2007) was used to make sure that physiological and other sources of noise were regressed out.

2.8. Statistical analyses

All statistical analyses were carried out using MATLAB R2020a (MathWorks, Natick, MA, USA). Data were assessed for normality using the Shapiro-Wilk test. Correction for multiple comparisons was implemented using False Discovery Rate (FDR) correction (Benjamini & Hochberg, 1995). Significance was set at $p < 0.05$. Given the non-random sampling approach necessitated by the specialized nature of the lifeguard population, results should be interpreted with caution regarding generalizability to the broader population.

2.9. Baseline variables

Between-group t-tests were carried out to determine baseline differences between controls and lifeguards in terms of age, forgetfulness, distractibility and false triggering.

2.10. Task performance variables

Between-group t-tests were carried out to determine differences between controls and lifeguards in terms of the 'correct', 'false positive' and NASA Task Load variables.

The impact of drowning detection training on the 'correct', 'false positive' and NASA Task Load variables was evaluated using paired t-tests comparing controls before (i.e., 'controls pre') and controls after (i.e., 'controls post') drowning detection training.

2.11. LEiDA

Leading Eigenvector Dynamics Analysis (LEiDA) is a computational approach that identifies recurring patterns of brain connectivity across time. The technique works by examining how different brain regions synchronize their activity at each moment during scanning, then clustering these patterns into distinct "brain states" that occur repeatedly throughout the session. Dynamic connectivity analyses were performed in MATLAB R2020a (MathWorks, Natick, MA, USA) using LEiDA scripts adapted from Cabral et al. (2017). For each of the $N = 105$ anatomical regions of interest (ROIs) extracted from the CONN toolbox (Whitfield-Gabrieli & Nieto-Castanon, 2012), the BOLD signal timeseries were averaged over all voxels within each ROI. These timeseries were demeaned and then Hilbert-transformed into an analytic signal which captures the time-varying phase of the BOLD fluctuations. This process resulted in a timeseries of BOLD phases for each ROI and each participant. Fig. 2a-b represents the BOLD phases of each ROI at timepoint $t = 1$ in cortical phase and in the complex plane.

Next, the degree of phase synchrony between pairs of brain regions was calculated at each timepoint t. This led to the computation of the dynamic phase-locking matrix (dPL(t)), which displays the degree of phase alignment between pairs of ROIs, across all $N = 105$ ROIs, for each participant and at each timepoint t. Phases of two brain regions are considered in full synchrony if their phase-locking value is 1, and out of synchrony if the value is -1. The leading eigenvector $V_1(t)$ was assessed for each dPL(t), to detect the primary pattern of phase synchrony with reduced dimensionality at each timepoint t. $V_1(t)$ contains $N = 105$ elements (i.e., ROIs), each having either a positive or negative value (Fig. 2c-d). When all phases exhibit a negative sign, it indicates that all phases are projecting onto $V_1(t)$ in the same direction, thus reflecting global coherence mode (Lord et al., 2019; Vohryzek et al., 2020). In contrast, elements with a positive sign represent phases projecting onto the opposite direction of $V_1(t)$. These positively-valued ROIs typically correspond to meaningful functional brain networks that dominate at a given timepoint t (Lord et al., 2019; Vohryzek et al., 2020).

K-means clustering was subsequently applied to all leading eigenvectors $V_1(t)$ to iteratively cluster similar patterns of brain activity into distinct states, ranging between $k = 5$ and $k = 12$ (Fig. 2e). Each calculation was repeated 10,000 times to enhance the stability of the results. In essence, this method minimizes the distance between each observation and the nearest cluster centroid. The Dunn score (Dunn, 1973) was then computed to identify the optimal k number of states that best explain the data by minimizing intra-cluster distances and maximizing inter-cluster distances.

To assign each LEiDA state to a meaningful reference label based on established functional networks (Yeo et al., 2011), we then calculated the proportion of ROIs that shared spatial overlap with each of the seven large-scale functional networks defined by Yeo's atlas. Following the methodology outlined in Vohryzek et al. (2020), this involved transforming each Yeo network into a vector made up of $N = 105$ elements that each reflected the extent of their contribution to each Yeo network. We then calculated Pearson's correlation coefficients between the centroids V_k and each Yeo network. Significance was set at $p < 0.01/k$. We then calculated the probability of occurrence of each state, defined as the fraction of timepoints during which a state is active during the scan. For each state, in line with previous work (Alonso Martínez et al., 2020; Cabral et al., 2017; Deco et al., 2019; Lord et al., 2019), permutation-based between-group t-tests were carried out to determine differences between controls and lifeguards; and permutation-based paired t-tests were run to identify differences between 'controls pre' and 'controls post', FDR-corrected. A total of 10,000 permutations were used to ensure stability of the results. It is worth noting that the k-means

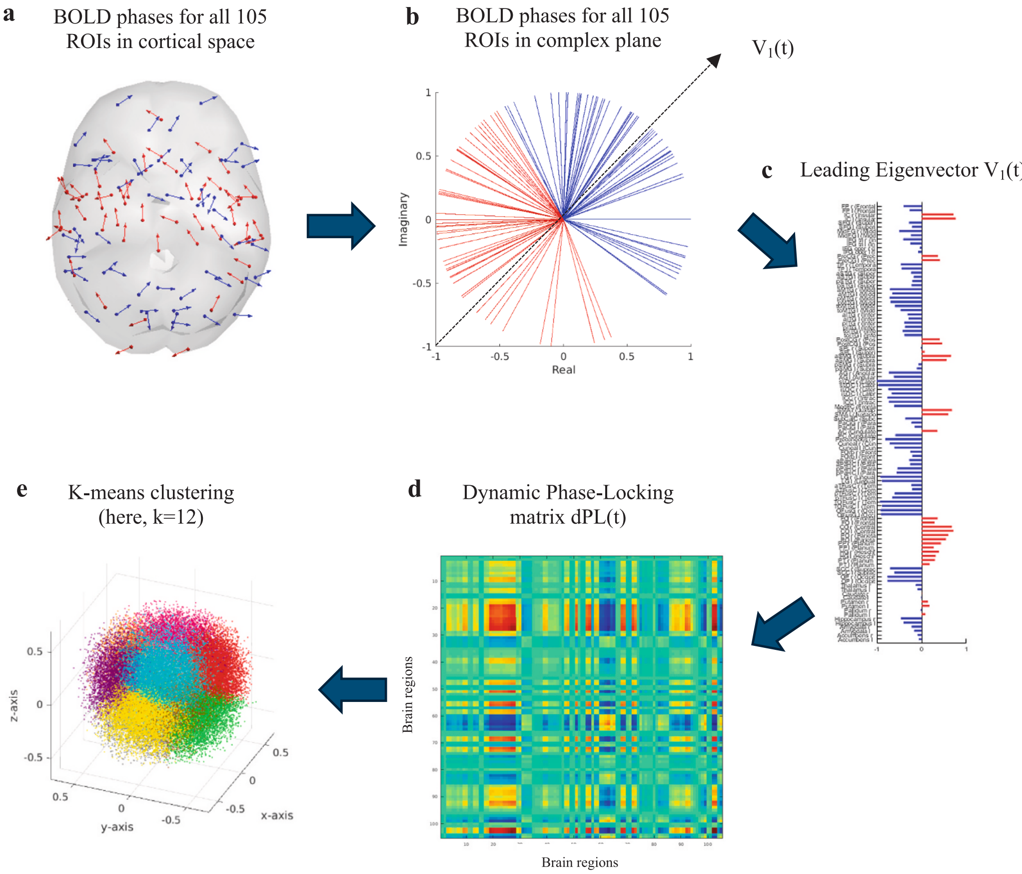

Fig. 2. Detection of recurring phase-locking patterns (or states) in fMRI signals. At each timepoint (here, at the first timepoint $t = 1$), the BOLD phase from each region of interest (ROI) is characterised by an arrow that indicates the phase orientation of that ROI and is positioned at the centre of gravity of that ROI (a) in cortical space and (b) in complex plane. The leading eigenvector (V_1) is depicted as a dashed arrow. (c) The horizontal bar plot displays the relative contribution of each ROI to V_1 at a given timepoint (here, the first volume $t = 1$). Phases are split into two communities (blue or red) based on their projection onto V_1. (d) The 105×105 dynamic phase-locking matrix dPL(t) shows the level of synchrony between pairs of ROI phases at a specific timepoint (here, the first volume $t = 1$). Warmer colours indicate greater synchrony between ROI phases. (e) All leading eigenvectors V_1 from all timepoints and all participants are clustered into k groups using k-means clustering ($k = 12$ in this case). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

clustering, Dunn score, spatial overlap, probability of occurrence, and t-tests steps were run twice, separately: once for the drowning detection task, and once for the resting-state data.

3. Results

3.1. Baseline variables

As illustrated in Fig. 3, there was no significant difference between controls and lifeguards in terms of age, forgetfulness, distractibility and false triggering ($p > 0.05$). These results confirm that baseline cognitive differences did not account for subsequent group differences in task performance or brain dynamics (Fig. 4).

3.2. Task performance variables

Between-group t-tests revealed no significant difference between ‘controls pre’ and lifeguards for ‘correct’, ‘false positives’ and NASA Task Load variables ($p > 0.05$). Paired t-tests revealed a significant increase in ‘correct responses’ (8.50 vs 9.44; $t_{(15)} = -1.99$, pFDR $= 0.02$) and a significant decrease in ‘effort’ ($t_{(15)} = 2.88$, pFDR $= 0.02$) between ‘controls pre’ and ‘controls post’. There was no significant difference between ‘controls pre’ and ‘controls post’ for ‘false positives’ and the other NASA Task Load variables. Importantly, when comparing ’controls post’ with lifeguards, trained controls showed numerically superior performance (9.44 vs 8.89 correct detections), though this difference did not reach statistical significance ($p > 0.05$). This suggests that specialized drowning detection training may enable novices to achieve performance levels comparable to, or potentially exceeding, experienced

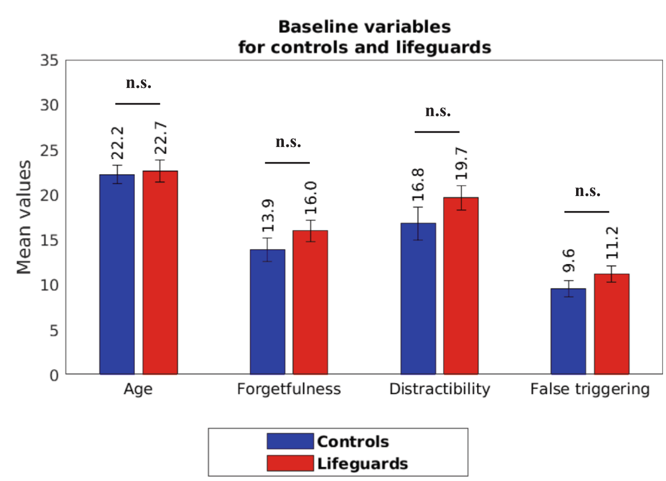

Fig. 3. Bar graph featuring the mean values of each baseline variable (i.e., age, forgetfulness, distractibility and false triggering), for each group (i.e., controls and lifeguards), with error bars (n.s. = non-significant).

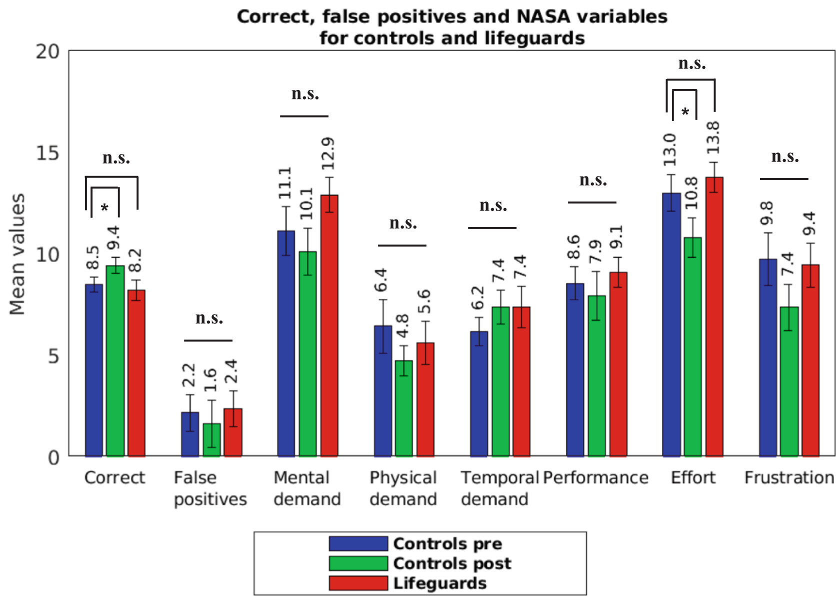

Fig. 4. Bar graphs illustrating the mean values of 'Correct', 'False positives' and each NASA Task Load variable (i.e., mental demand, physical demand, temporal demand, performance, effort, frustration), for each group (i.e., 'controls pre', 'controls post' and 'lifeguards'), with error bars (n.s. = non-significant; * = pFDR < 0.05).

lifeguards.

3.3. LEiDA

3.3.1. Drowning detection task

The Dunn scored revealed that the optimal number of states that best explain the drowning detection fMRI data is 12. In the following analyses, we will label each of these 12 states as "state D" followed by the state number, "D" referring to "drowning".

Fig. 5 displays the rendering of each state on the cortex. The areas highlighted in brown correspond to brain regions that are in synchrony with each other and that positively project onto V_1 for a given state.

State D3 did not significantly correlate with any network, and therefore can referred to as the global coherence network. State D1 significantly correlated with the dorsal attention ($r = 0.23$) and Default Mode ($r = 0.25$) networks; state D2, with the dorsal attention ($r = 0.56$) and frontoparietal ($r = 0.41$) networks; state D4, with the Default Mode network ($r = 0.67$); state D5, with the visual network ($r = 0.77$); state D6, with the frontoparietal network ($r = 0.73$); state D7, with the somato-motor network ($r = 0.53$); state D8, with the somato-motor network ($r = 0.69$); state D9, with the visual network ($r = 0.61$); state D10, with the ventral attention network ($r = 0.74$); state D11, with the dorsal attention network ($r = 0.47$), and state D12, with the Default Mode network ($r = 0.37$).

As illustrated in Fig. 6, there was a significant difference in probability of occurrence between 'controls pre' and 'controls post' (9.0 % vs 6.4 %; $t_{(15)} = 3.72$, pFDR = 0.003) and between 'controls pre' and 'lifeguards' (9.0 % vs 6.4 %; $t_{(15)} = 2.79$, pFDR = 0.047) for the frontoparietal network (i.e., state D6). There was no significant difference in probability of occurrence between groups and within group for any of the other 11 states ($p > 0.05$).

3.3.2. Resting-state

For the resting-state sequence, the optimal number of states identified by the Dunn score following k-means clustering analyses was 6. In the following analyses, we will label each of these 6 states as "state R" followed by the state number, "R" referring to "resting-state".

Fig. 7 displays the rendering of each state on the cortex.

State R5 did not significantly correlate with any network, and therefore can referred to as the global coherence network. State R1 significantly correlated with the somato-motor ($r = 0.65$) and ventral attention networks ($r = 0.55$); state R2, with the Default Mode Network ($r = 0.50$); state R3, with the frontoparietal network ($r = 0.57$); state R4, with the dorsal attention network ($r = 0.72$); and state R6, with the visual network ($r = 0.68$).

As illustrated in Fig. 8, there was a significant difference in probability of occurrence between 'controls pre' and 'controls post' (13.2 % vs 17.8 %; $t_{(15)} = -2.07$, pFDR = 0.026) for the somato-motor and ventral attention networks (i.e., state R1). There was also a significant difference between 'controls pre' and 'controls post' (25.0 % vs 17.3 %; $t_{(15)} = 1.75$, pFDR = 0.046) and between 'controls pre' and 'lifeguards' (25.0 % vs 14.0 %; $t_{(15)} = 1.74$, pFDR = 0.044) for the Default Mode Network (i.

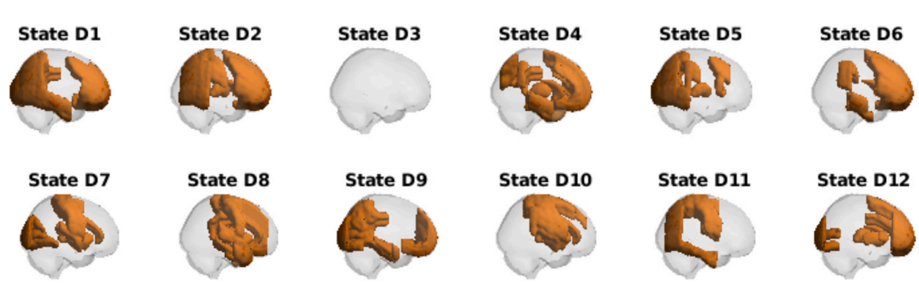

Fig. 5. Rendering of brain regions with positive projections onto V_1 for each of the k = 12 states, for the drowning detection task.

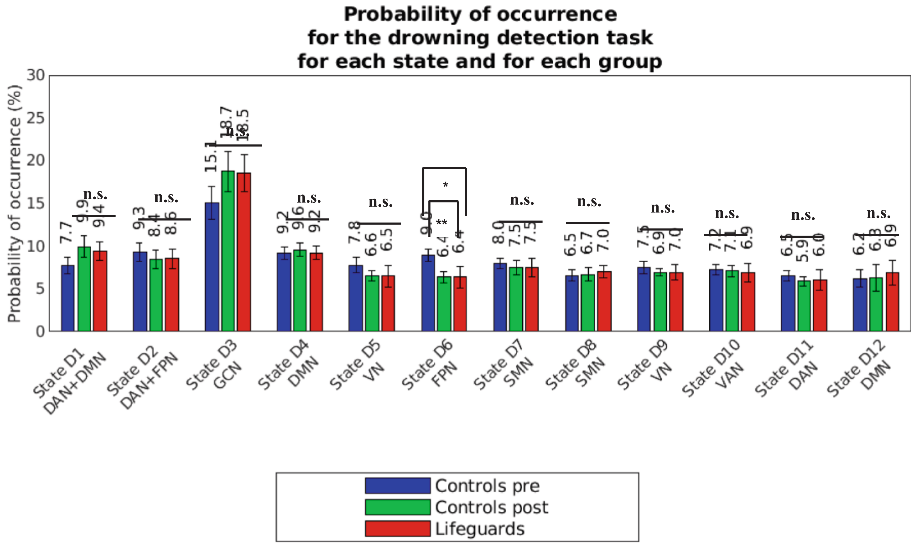

Fig. 6. Bar graph representing the probability of occurrence of each state, for each group, for the drowning detection task, with error bars (n.s. = non-significant; * = pFDR < 0.05; ** = pFDR < 0.01). DAN = dorsal attention network; DMN = Default Mode Network; GCN = global coherence network; VN = visual network; FPN = frontoparietal network; SMN = somato-motor network; VAN = ventral attention network.

Fig. 7. Rendering of brain regions with positive projections onto V_1 for each of the k = 6 states, for the resting-state sequence.

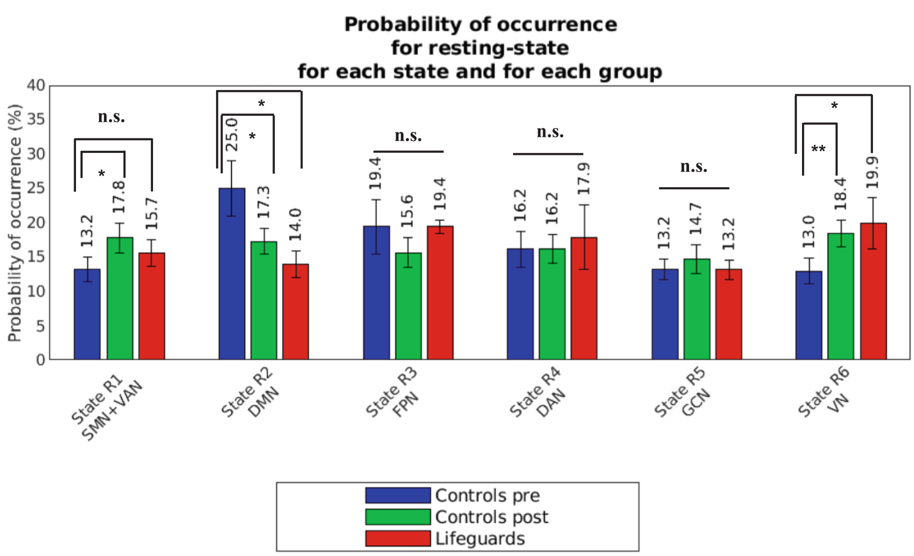

Fig. 8. Bar graph representing the probability of occurrence of each state, for each group, for the resting-state sequence, with error bars (n.s. = non-significant; * = pFDR < 0.05; ** = pFDR < 0.01). SMN = somato-motor network; VAN = ventral attention network; DMN = Default Mode Network; FPN = frontoparietal network; DAN = dorsal attention network; GCN = global coherence network; VN = visual network.

e., state R2). Finally, there was also a significant difference between ‘controls pre’ and ‘controls post’ (13.0 % vs 18.4 %; $t_{(15)} = -2.48$, pFDR = 0.009) and between ‘controls pre’ and ‘lifeguards’ (13.0 % vs 19.9 %; $t_{(15)} = -2.19$, pFDR = 0.021) for the visual network (i.e., state R6). There was no significant difference in probability of occurrence between groups and within group for any of the other 3 states ($p > 0.05$).

4. Discussion

The present study employed a two-part experimental design to investigate neural mechanisms underlying drowning detection expertise. Study 1 compared brain function between experienced lifeguards and novice controls, while Study 2 examined training-induced changes in brain dynamics within the control group.

4.1. Study 1: between-group differences (Lifeguards vs. Controls)

Our Study 1 findings provided mixed support for our hypotheses, with some supported and others not supported based on statistical significance testing. Contrary to our first hypothesis, we did not find a significant difference in drowning detection performance between controls and lifeguards at baseline. This unexpected finding may be attributed to the shortened 30-minute task duration necessitated by MRI constraints, compared to the standard 60-minute protocols used in previous lifeguard research (Sharpe et al., 2024). The reduced task duration may have limited cognitive fatigue effects that typically distinguish expert from novice performance in sustained attention tasks. Despite the absence of behavioural differences, we observed significant neural differences between groups. Specifically, lifeguards showed reduced recruitment of the frontoparietal network during the drowning detection task compared to controls at baseline. The frontoparietal network is critically involved in effortful cognitive control and complex problem-solving (Botvinick & Cohen, 2014; Duncan, 2010). The reduced activation in lifeguards suggests more efficient neural processing, requiring less effortful cognitive control to achieve similar performance levels. This pattern is consistent with expertise research showing that experts often demonstrate more efficient brain function, achieving equivalent or superior performance with reduced neural effort (Kempton et al., 2011). At rest, lifeguards exhibited significantly lower activation of the Default Mode Network compared to controls. The Default Mode Network is associated with mind-wandering and internally-directed attention (Mason et al., 2007), and its reduced activation in experts suggests enhanced capacity for maintaining focused, externally-directed attention even during rest periods.

4.2. Study 2: training effects within controls

Our Study 2 findings supported our hypotheses based on statistical significance testing. The main goals of this part of the study were to explore changes in brain networks associated with drowning detection training in the control group. Our results showed a significant improvement in drowning detection performance (i.e., number of correctly identified drowning events) in the control group after drowning detection training compared to before, which is in line with the results of Sharpe et al. (2025). Notably, trained controls showed numerically superior performance compared to lifeguards, though this difference did not reach statistical significance. While this preliminary finding suggests potential for specialized training to enhance novice performance, the non-significant difference and study limitations necessitate cautious interpretation and replication before drawing definitive conclusions about training effectiveness relative to existing lifeguard expertise. At the neural level, training-induced changes in controls resulted in brain activation patterns that closely resembled those observed in lifeguards. More specifically, the probability of occurrence of the frontoparietal network decreased within the control group after training, reaching a similar value to that of the lifeguards. This could reflect that, before training, controls had to make more effort than after training to reach a drowning detection performance that resembles that of the lifeguards. Similar findings have previously been observed in the context of dehydration in healthy adolescents (Kempton et al., 2011). Dehydrated participants exhibited an increased BOLD response in the frontoparietal network during an executive function task (i.e., Tower of London) in order to achieve the same level of performance as before dehydration, which the authors interpreted as a suboptimal use of brain energy after dehydration (Kempton et al., 2011). In particular, the frontoparietal network has typically been associated with effortful cognitive control and complex problem solving (Botvinick & Cohen, 2014; Duncan, 2010). In fact, in the present study, in addition to displaying reduced recruitment of the frontoparietal network after training, controls also scored significantly lower on the 'effort' subscale of the NASA questionnaire, suggesting that they found the task easier to carry out after training. Regarding resting-state, we observed within-group and between-groups differences in the recruitment of three different LEiDA states, providing insights into how training reshapes baseline brain function.

First, there was a significant increase in the recruitment of the somato-motor and ventral attention networks (i.e., state R1) in controls after training, compared to before. The ventral attention network is a stimulus-driven network known for its role in reorienting attention towards unexpected salient cues (Seeburger et al., 2024). In a *meta*-analysis, Kim (2014) showed that this network is essential for maintaining alertness and being able to swiftly detect and respond to significant changes in the environment. In conjunction with the somato-motor network, the ventral attention network supports adaptive and responsive behaviours, sending signals to the motor cortex to execute appropriate motor responses (Herman et al., 2020), which are essential lifeguarding skills (Sharpe et al., 2023; 2024). Second, we observed a significant decrease in the probability of occurrence of the Default Mode Network (i.e., state R2) within the control group after training. Additionally, lifeguards exhibited significantly lower recruitment of that network compared to controls at baseline. Increased activation of the Default Mode Network has typically been associated with mind wandering (Mason et al., 2007) and reduced performance on attention-related tasks (Hinds et al., 2013). Together with greater recruitment of the ventral attention network, decreased activation of the Default Mode Network has previously been observed in practitioners of attention-based meditation (Brefczynski-Lewis et al., 2007; Brewer et al., 2011), suggesting that increased sustained attention is associated with Default Mode network suppression combined with ventral attention network activation (Pamplona et al., 2020). Finally, we observed a significant increase in the recruitment of the visual network (i.e., state R6) within the control group after training compared to before, as well as a significantly higher activation of that network in the lifeguards compared to the controls at baseline. The visual cortex is known for playing an essential role in attentional control and spatial attention in the context of visual search tasks (Connolly et al., 2016), suggesting that training may enhance visual processing capabilities relevant to drowning detection.

4.3. Implications for drowning prevention and lifeguard training

The findings from both studies have important implications for understanding how specialized training can enhance drowning detection capabilities and inform evidence-based approaches to lifeguard training programs. Our results suggest that current lifeguard certification training, while valuable, may not fully optimize drowning detection capabilities. The preliminary finding that trained novices achieved numerically similar performance levels to certified lifeguards, while not statistically significant, suggests potential areas for exploration in training protocols. However, given the study's limitations including small sample size, shortened task duration, and laboratory setting, these findings should be interpreted cautiously and require replication in larger, more ecologically valid studies before informing changes to established training protocols. Any modifications to current lifeguard certification standards would require extensive validation in real-world settings to ensure community safety is maintained. The neural efficiency observed in both lifeguards and trained controls provides insights into the mechanisms underlying expertise in surveillance tasks. The reduced frontoparietal network activation and decreased Default Mode Network activity suggest that effective training should focus on developing automatic, less effortful detection processes while minimizing mind-wandering tendencies. These findings could inform the development of training programs that specifically target these neural mechanisms. Furthermore, the observed changes in resting-state brain dynamics suggest that effective training produces lasting changes in baseline brain function, not just task-specific improvements. This indicates that well-designed training programs may have benefits that extend beyond the specific trained task, potentially improving overall attentional capabilities.

It is crucial to emphasize that these findings should not be interpreted as evidence that novice individuals with brief training can replace certified lifeguards in real-world scenarios. Lifeguard certification encompasses numerous critical skills beyond drowning detection, including water rescue techniques, first aid, CPR, and emergency response protocols that were not assessed in this study. The controlled laboratory environment and specific task parameters may not generalize to the complex, dynamic conditions of actual aquatic environments where lifeguards operate. Therefore, while these findings provide valuable insights into the neural mechanisms underlying surveillance training, they should be considered preliminary evidence requiring extensive replication and validation before informing any changes to established safety protocols.

4.4. Ecological validity and real-world applications

While our laboratory-based drowning detection task provided important insights into the neural mechanisms of surveillance expertise, we acknowledge significant limitations in ecological validity that must be considered when interpreting these findings for real-world applications. The controlled laboratory environment necessarily omitted many factors that characterize real-world lifeguarding scenarios. These include environmental distractions (noise, weather conditions, glare), three-dimensional water movement, varying lighting conditions, social interactions with swimmers, and the physical demands of continuous surveillance in outdoor environments. Additionally, real-world drowning incidents may present with different characteristics than our standardized simulated events. Despite these limitations, several aspects of our findings do have ecological relevance. The sustained attention demands, visual search requirements, and the need to detect rare but critical events in our task mirror key aspects of real-world lifeguarding. The neural efficiency patterns we observed align with expertise research in other domains and provide mechanistic insights that could inform training approaches. However, the practical implications of our findings for drowning prevention efforts should be interpreted cautiously. While our results suggest that specialized training can enhance drowning detection performance and neural efficiency, the translation to real-world effectiveness requires validation in naturalistic settings. The finding that bathers re-emerged after drowning events in our simulation, while necessary for experimental control, represents a significant departure from reality that may have influenced detection strategies and performance patterns.

5. Limitations

Several limitations of this study warrant consideration. Firstly, the 30-minute task duration, necessitated by MRI constraints, may have limited our ability to detect drowning detection performance differences between groups, particularly given that standard protocols typically employ 60-minute tasks (Sharpe et al., 2024). This shortened duration may have reduced the cognitive fatigue typically experienced during longer surveillance periods, potentially masking differences in sustained attention capabilities between lifeguards and controls. Secondly, our relatively small sample size (18 lifeguards and 16 controls) necessitates caution in interpreting the results and limits the generalizability of our findings. While our sample size is comparable to similar neuroimaging studies, a larger sample would increase statistical power and allow for more nuanced analyses of individual differences in training response. Thirdly, the controlled laboratory environment of the MRI scanner, while necessary for neuroimaging, lacks the ecological validity of real-world aquatic environments. The absence of dynamic factors such as changing light conditions, water movement, and environmental distractions may have influenced both drowning detection performance and neural activation patterns. Additionally, the use of video stimuli, while standardized, may not fully capture the multisensory experience of real-world lifeguarding, potentially affecting the engagement of certain neural networks. Future research should address these limitations to enhance the robustness and applicability of these findings to real-world lifeguarding scenarios. Fourth, the novice group carried out the task twice, once before and once after training, whereas the lifeguard group completed it only once. This design limitation makes it challenging to confirm with certainty whether the observed changes in the novice group were due to the effectiveness of the drowning detection training or if they were simply the result of practice effects and greater familiarity with the specific simulation used for testing. Future studies should address this limitation by either including an additional control group that would complete the task twice without receiving additional training, or by having the lifeguard group carry out the task twice as well. Fifth, the non-random participant selection, necessitated by the specialized nature of the lifeguard population, limits the generalizability of our findings to the broader population. Our results should be interpreted as exploratory findings that require replication in larger, more diverse samples. Furthermore, the non-random sampling approach and potential for participant interactions during the study period limit the generalizability of findings to the broader population and may have influenced results in ways that standard hypothesis testing cannot fully account for. The statistical significance observed should be interpreted within the context of these sampling limitations and the exploratory nature of this research.

5.1. Possible future directions

Building upon the findings and limitations of the current study, several promising directions for future research emerge. To enhance ecological validity, future studies should assess the effectiveness of drowning detection training in more naturalistic settings, potentially through immersive virtual reality environments that simulate real-world conditions such as fluctuating lighting, water movement, and external distractions. Investigating the translation of laboratory-based improvements to actual lifeguarding performance in operational contexts would also be valuable. Longitudinal research tracking the long-term effects of training on neural plasticity and performance could offer insights into the sustainability of training-induced changes and inform the timing and necessity of refresher programs. Combining fMRI with other neuroimaging modalities like EEG or MEG may yield a more nuanced understanding of the spatial and temporal dynamics of brain activity during drowning detection tasks, particularly when used alongside VR-based simulations. Moreover, examining individual differences, such as prior experience, cognitive profiles, and personality traits, could clarify why some individuals benefit more from training than others. Future studies should also incorporate additional control groups, such as those completing the task without any training or receiving unrelated attention-based interventions, to better isolate training-specific effects. Research into optimizing training protocols, including ideal frequency, duration, and content, may help refine educational strategies, while evaluating whether specialized training can further enhance the performance of already-certified lifeguards could support ongoing professional development. Finally, with the rise of AI-assisted drowning detection systems, exploring how neural and behavioural findings from this research can inform the design and integration of such technologies, and studying the brain dynamics of lifeguards working in tandem with AI, offers an exciting and innovative avenue for future investigation.

6. Conclusion

Taken together, our findings from both Study 1 (between-group comparisons) and Study 2 (training effects) provide converging evidence that specialized drowning detection training can effectively reshape attention-related brain networks and improve performance in drowning detection tasks. Our results highlight that training improves how efficiently the brain processes information during hazard detection tasks and makes it less effortful for individuals to stay on task, as reflected by a reduction in the occurrence of the frontoparietal network and a decrease in self-reported 'effort' levels after training. In fact, after training, the recruitment of the frontoparietal network in controls reached a similar pattern of activity to that observed in lifeguards, suggesting that targeted training can induce expertise-like neural efficiency patterns. The preliminary finding that trained novices achieved numerically similar performance levels to experienced lifeguards, while not statistically significant, provides initial insights that warrant further investigation in larger, more ecologically valid studies. Given the study's limitations including laboratory setting, shortened task duration, and small sample size, these findings should be interpreted as exploratory rather than definitive. Any consideration of modifications to current lifeguard training protocols would require extensive validation in real-world settings with larger samples to ensure the safety and effectiveness of drowning prevention efforts. In addition, our results also revealed that drowning detection training lessens mind-wandering patterns of brain activity at rest, while increasing activity in regions responsible for bottom-up responses to unexpected stimuli arising from the external environment, which is a key lifeguarding skill. These resting-state changes suggest that effective training produces lasting alterations in baseline brain function that may enhance overall attentional capabilities. However, the translation of these laboratory-based findings to real-world drowning prevention efforts requires careful consideration of ecological validity limitations. While our results provide valuable mechanistic insights into the neural basis of surveillance expertise, validation in naturalistic settings is essential before implementing widespread changes to training protocols. These findings provide valuable insights into how specialized training shapes neural mechanisms and may improve drowning detection performance in critical lifesaving scenarios. Future research addressing the ecological validity limitations identified in this study will be essential for translating these findings into effective real-world drowning prevention strategies.

CRediT authorship contribution statement

Marie-Stephanie Cahart: Writing – review & editing, Writing – original draft, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation. **Marcus S. Smith:** Writing – review & editing, Investigation, Conceptualization. **Benjamin T. Sharpe:** Writing – review & editing, Resources, Conceptualization. **Steven C.R. Williams:** Writing – review & editing, Resources, Investigation, Conceptualization. **Simon Hill:** Writing – review & editing, Software, Resources, Methodology. **Jo Talbot:** Writing – review & editing, Resources, Conceptualization. **Nick Grazier:** Writing – review & editing, Resources, Conceptualization. **David J. Lythgoe:** Writing – review & editing, Resources, Methodology. **Jenny Smith:** Writing – review & editing, Resources, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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