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Blue screen filters reduce visual discomfort and disrupt the relationship between neural and subjective responses to unnatural images☆

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ABSTRACT

Heightened sensory sensitivity, including visual discomfort, is common in migraine, autism, and the wider population, and is linked to headaches, perceptual disturbances, and reduced quality of life. We tested whether coloured screen filters reduce visual discomfort and whether such effects are reflected in neural responses. Nineteen participants with self-identified sensory sensitivity completed a within-subject task viewing natural scenes, striped gratings, and filtered-noise "bump" textures under greyscale, red, and blue screen filters. Subjective discomfort was rated after each trial, and neural responses were measured with EEG steady-state visual evoked potentials (SSVEPs) at 5 Hz. Image type strongly influenced both ratings and SSVEP amplitude. Blue screen filters lowered discomfort ratings for stripes and bumps but did not reliably affect SSVEP amplitude. The positive association between SSVEP amplitude and discomfort was weaker under blue screen filtering, suggesting a change in how neural activity is related to subjective experience in this modest sample. These results indicate that broad chromatic manipulations may not reduce cortical responses *per se*, but may alter the mapping between neural responses and discomfort.

1. Introduction

1.1. What is sensory sensitivity and why does it matter?

Sensory sensitivity is characterised by heightened responsiveness to everyday stimuli, leading to overstimulation and strong subjective or physiological reactions (Kurczewska et al., 2024; Ward, 2019). Individuals with visual discomfort commonly report eye strain, visual distortions, and headaches when viewing high-contrast or repetitive patterns or bright lights (Wilkins, 1995). Sensory responses also vary widely across individuals in the general population (Aron et al., 2012; Ward, 2019).

Heightened sensitivity to sensory input is widespread, with approximately 20% of the general population reporting elevated responses to everyday stimuli and values of up to 90% documented in some neurodivergent samples (Greven et al., 2024; Schoen, 2009).

Despite this prevalence, terminology is inconsistent. Labels such as *sensory processing sensitivity*, *sensory over-responsivity*, and *visual discomfort* are often used interchangeably, although they describe related but distinct concepts. *Visual discomfort* is typically used to refer specifically to negative reactions to visual patterns such as flicker, stripes, or glare (Wilkins, 1995). Here, we use heightened sensory sensitivity as an umbrella term for increased reactivity to sensory input more broadly and visual discomfort for adverse responses to visual patterns.

Sensory sensitivity is often elevated in a range of clinical and neurodivergent groups, including autism (Robertson & Baron-Cohen, 2017), ADHD (Tavassoli et al., 2014), functional neurological disorder (Ranford et al., 2020) and migraine (Demarquay & Mauguière, 2016; Lévêque et al., 2020). It is possible to trigger migraine attacks with visual stimuli, and people with migraine tend to experience more discomfort from striped patterns (Harle et al., 2006; Shepherd et al., 2013). In autism, environmental and sensory barriers to successful work have been documented (Pfeiffer et al., 2017), and autism-like traits in non-clinical groups are also linked to sensory sensitivity (Robertson & Simmons, 2013). Visual discomfort is reported to be increased in other conditions associated with heightened cortical sensitivity, such as fibromyalgia, persistent postural dizziness and ADHD, and people with

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traumatic brain injury often report photophobia that can be alleviated through colour interventions (BarNir et al., 2023; Powell et al., 2022; Ten Brink & Bultitude, 2022; Tosta et al., 2024). Some individuals with dyslexia report increased visual discomfort, but dyslexia and visual stress are not synonymous. Many people with dyslexia do not experience visual stress, and many individuals who report visual stress can read normally (Wilkins et al., 2016). This likely reflects the fact that dyslexia encompasses heterogeneous sources of reading difficulty, many of which are non-visual and frequently involve phonological processing deficits (Schwarz et al., 2024).

1.2. Sensory environment design

Sensory sensitivity is linked to reduced quality of life, especially in environments that overwhelm the senses (Costa-López et al., 2021). Uncomfortable visual stimuli are common in built environments, including classroom and office interiors (Boyce & Wilkins, 2018), architectural façades (Le et al., 2017), and repetitive patterns inside buildings, such as geometric flooring and tiling (Valentine et al., 2025; Wilkins et al., 2018). Taken together, these findings highlight the need for more intentional sensory design of public spaces that accommodate people with heightened sensory sensitivity (Martin & Wilkins, 2022).

For example, classrooms can present a harsh visual atmosphere due to factors such as high colour contrasts, dense visual decoration and fluorescent lighting (Winterbottom & Wilkins, 2009). As it is thought that autistic people experience sensory overload (MacLennan et al., 2023), these design choices may be particularly problematic. There are strong colour preferences in autistic people (Ludlow et al., 2014), although there seems to be less accurate perception of colour (Franklin et al., 2008). Despite the complex pattern in the literature, muted colours have been suggested as beneficial in sensory environments designed to support this population (Ming En et al., 2026). To examine sensory sensitivity in a structured way, we use Ward (2019)'s three-dimensional model, which distinguishes subjective, behavioural, and neural aspects.

1.3. The three-dimensional framework: Subjective, behavioural, neural sensory sensitivity

To examine sensory sensitivity more systematically, we follow Ward (2019)'s three-dimensional model as our organising framework. *Subjective* sensitivity refers to self-reported experiences such as pain, discomfort, or visual illusions. For example, migraine aura can involve flashes of light, flickering, or "teichopsia" (zigzag patterns) (Lane & Reynolds, 2019). Hyperresponsive individuals may be overwhelmed by sensations, such as discomfort from certain fabrics, whereas hyporesponsive individuals may seek intense sensory input (Lane & Reynolds, 2019). *Behavioural* sensitivity refers to differences in detection or discrimination between stimuli. Subjective sensitivity and behavioural sensitivity capture different aspects of how people respond to sensory input, for example, autistic people tend to be less able to discriminate colours compared to control populations (Franklin et al., 2008). *Neural* sensitivity refers to measurable brain activity evoked by uncomfortable stimuli, such as heightened responses in primary visual cortex to high-contrast or flickering patterns (Gentile & Aguirre, 2020; Wilkins & Hibbard, 2014). Neural sensitivity can also diverge from subjective experience, as people with photosensitive epilepsy do not always report pain during a seizure despite a large neural response, and may even use visual stimuli to induce seizures (Brinciotti et al., 2021).

Together, these three dimensions capture how sensitivity varies between groups, across different stimuli, and between individuals (Ward, 2019). Subjective sensitivity is often assessed with questionnaires that capture experiences over time (Braithwaite et al., 2015; Conlon et al., 1999; Perenboom et al., 2018; Price et al., 2025; Robertson & Simmons, 2019), or with trial-based measures taken during or immediately after stimulus presentation. The Pattern Glare Test is the most widely used paradigm for assessing visual discomfort (Wilkins & Evans, 2001), alongside tasks such as two-alternative forced-choice judgements and rating scales collected during neuroimaging experiments (O'Hare, 2017; O'Hare & Hibbard, 2011). Neural correlates of these subjective measures can be recorded simultaneously, for example with EEG or fNIRS, which enables direct comparison between brain responses and self-reported discomfort (Haigh et al., 2013; O'Hare, 2017; O'Hare & Hibbard, 2024). By distinguishing subjective, behavioural and neural sensitivity, this framework highlights the need to understand which neural processes underlie sensory sensitivity and why some visual stimuli are more uncomfortable than others (Ward, 2019). One proposed mechanism is excitation–inhibition imbalance.

1.4. Mechanistic explanation I: Excitation–inhibition imbalance

The excitation–inhibition model described by Rubenstein and Merzenich (2003) proposes that heightened sensory sensitivity in autism may result from an imbalance between excitatory and inhibitory neural mechanisms. Excitatory and inhibitory activity can be considered at multiple levels. At the neurotransmitter level, reduced GABA concentrations have been associated with sensory sensitivity (O'Hare, Tarasi et al., 2023), and at the systems level, oscillatory brain activity has also been linked to sensory sensitivity (Manyukhina et al., 2021). Although excitation and inhibition can have several meanings, one definition refers to the balance between excitatory (glutamatergic) and inhibitory (GABAergic) neurotransmitter activity, which is maintained through developmental and homeostatic processes across individual neurons and cortical circuits (Sohal & Rubenstein, 2019; Sturgill & Isaacson, 2015). This imbalance may lead to heightened sensory responsiveness and difficulties filtering out irrelevant stimuli (Takarae & Sweeney, 2017). Excitation-inhibition imbalance has therefore been proposed as a neural mechanism contributing to the pathophysiology of sensory sensitivity in autism (Chen et al., 2020; Dunn & Jones, 2020; Robertson & Baron-Cohen, 2017) and migraine (O'Hare, Tarasi et al., 2023; Vecchia & Pietrobon, 2012) and, more broadly, in explaining why some visual stimuli are more uncomfortable than others (Penacchio et al., 2023).

Studies that use oscillatory gamma-band activity as an index of excitation–inhibition balance have not found a clear relationship with sensory sensitivity (Sumner et al., 2026). Other studies have also failed to demonstrate neurotransmitter imbalances associated with oversensitivity in the auditory domain (Ward et al., 2025).

Although the excitation–inhibition imbalance model would predict greater discomfort in some groups than in others, it does not identify which specific stimulus features are likely to trigger discomfort or heightened responses in susceptible individuals. An alternative account is efficient coding theory, which explains sensory sensitivity in terms of how the visual system is optimised to process the statistical properties of natural scenes. From this perspective, discomfort arises when stimuli deviate from these expected statistics, placing greater demands on neural processing (O'Hare & Hibbard, 2024; Penacchio & Wilkins, 2015).

1.5. Mechanistic explanation II: Inefficient coding and visual discomfort

Efficient coding theory (Attneave, 1954; Barlow et al., 1961) proposes that sensory neurons are adapted to encode input efficiently by minimising redundancy and maximising novel information (Field, 1994). The visual system is therefore optimised for images with the statistical structure of natural scenes (Olshausen & Field, 2004). When stimuli deviate from these statistics, they become inefficient to encode (Wilkins, 2012), placing greater demands on neural processing and leading to cortical hyperexcitation and discomfort (Hibbard & O'Hare, 2015; Penacchio et al., 2023; Penacchio & Wilkins, 2015).

Uncomfortable stimuli often share this property: high-contrast gratings (Wilkins et al., 1984), large chromatic separations (Haigh et al.,

2018; Lindquist et al., 2021), and flicker (Gentile & Aguirre, 2020) all diverge from natural scene statistics. Filtered-noise textures provide further evidence: when their statistics are shifted away from natural norms, they are rated as more uncomfortable, both in greyscale (Fernandez & Wilkins, 2008; O'Hare & Hibbard, 2011) and in colour (Juricevic et al., 2010). Specifically, narrow-band repetitive striped patterns with midrange spatial frequencies, and images filtered to have an increased energy at midrange to high spatial frequencies (Conlon et al., 2001; Fernandez & Wilkins, 2008; Hibbard, Allen et al., 2026; Wilkins et al., 1984), have been associated with increased discomfort, albeit with potentially complex interactions with overall contrast, spatial frequency profile and flicker (Hibbard, Asher et al., 2026; O'Hare & Hibbard, 2024). Importantly, these artificial stimuli lack semantic content, which suggests that discomfort arises from low-level statistics rather than meaning.

Computational models support this account. Simulations based on signal processing principles reproduce neural responses to uncomfortable stimuli, showing that inefficient inputs increase response variability and metabolic cost (Hibbard & O'Hare, 2015; Penacchio & Wilkins, 2015; Sinno & Bovik, 2018). They also show reduced sparseness, which is another marker of hyperexcitation (Penacchio et al., 2023). Efficient coding theory therefore links deviations from natural statistics to subjective discomfort and predicts that images with properties that cannot be efficiently processed will trigger greater discomfort. These mechanisms also extend to real-world environments, where architecture, lighting, or repetitive patterns can impose similar processing demands and cause discomfort (Boyce & Wilkins, 2018; Le et al., 2017; Wilkins et al., 2018).

1.6. Colour and sensory experience

Colour is a prominent feature of visual environments and is often manipulated in practice to reduce discomfort and support sensory regulation. Colours and patterns whose statistics align with the brain's expectations of natural stimuli, such as clear skies or green forest scenery, have been proposed to produce more optimal neural responses (Olszewska-Guizzo et al., 2022). Naturalistic blues and greens might therefore be expected to feel more comfortable than less familiar chromatic combinations. In particular, sky-like blue tones are often assumed to be calming and visually comfortable (Nair et al., 2022; O'Connor, 2011; Pence et al., 2019).

It has been suggested that colour therapy may be beneficial for mitigating sensory sensitivity, however the findings supporting the use of colour therapy and blue lighting are often anecdotal (O'Connor, 2011). Clinical approaches such as precision tints and coloured overlays are also used to modulate visual discomfort, but evidence for their effectiveness is mixed and complicated by strong individual differences in colour preferences and perception (Franklin et al., 2008; Griffiths et al., 2016; Harkin et al., 2024; Hoggan et al., 2016; Ludlow et al., 2014; Maule et al., 2017). Overall, empirical findings are inconsistent, with some studies reporting positive outcomes and others reporting little or no effect (Nair et al., 2022; Pence et al., 2019), and several studies suffer from methodological limitations such as small sample sizes and the presence of comorbid disorders within participant groups (Pence et al., 2019).

1.7. Rationale and hypotheses

Discomfort from visual stimuli may arise from inefficient coding, whereby stimuli that deviate from the statistical properties of everyday images place greater processing demands on the visual system. Some people may be more susceptible to this than others, possibly reflecting imbalances in neural excitation and inhibition. Colour has also been found to influence visual discomfort (Haigh et al., 2013; O'Hare et al., 2023), with both anecdotal reports and experimental evidence suggesting that certain colours, such as blueish hues, are more pleasant and less arousing than others (Valdez & Mehrabian, 1994).

We selected blue and red screen filters to represent opposite extremes of the visible spectrum. Blue light is known to exert strong physiological effects in other domains, such as alertness and cognition (Vandewalle et al., 2009). Conversely, a Cochrane review suggested that blocking blue light has little to no effect on visual performance and reported visual fatigue (Singh et al., 2023). Red provided the complementary long-wavelength contrast at the other end of the spectrum. Red light has been shown to result in increased arousal compared to green (Wilson, 1966), and red light has been shown to increase arousal compared to yellow, green, and blue, with the latter producing the least arousal (Jacobs & Hustmyer, 1974). In epilepsy patients, red light is typically more epileptogenic (Fisher et al., 2022; Gasparini et al., 2025; Parra et al., 2007). Red served as a comparator to blue, enabling us to examine whether spectral opposites differ in their influence on discomfort and neural responses. Together with a greyscale control (no screen filter), these conditions provided a direct test of whether broad colour manipulations measurably affect neural responses associated with visual discomfort.

Using established methods from O'Hare and Hibbard (2024), we measured both neural responses (steady-state visual evoked potentials; SSVEP) and subjective discomfort ratings for three classes of images: natural scenes (typical environmental statistics), stripes (high-contrast sinusoidal gratings) and bumps (filtered noise textures). The experiment was conducted in a dark room, with the screen providing the sole source of illumination. Applying blue, red or greyscale screen filters altered the spectral composition of the emitted light, thereby changing the overall ambient appearance of the room. The primary aim was to determine whether coloured screen filters reduce visual discomfort and neural activity, as measured by subjective ratings and SSVEP amplitude. Secondary aims were to examine whether discomfort varies systematically by image type, to investigate spatial frequency effects for artificial stimuli, and to assess the correspondence between neural and subjective measures of discomfort. Based on this we tested the following four hypotheses:

- H1 Filter colour would modulate discomfort and SSVEP amplitude, with blue and red filters producing lower values than greyscale (if colour in general reduces discomfort) and blue lower than red (due to the pleasant and less arousing effects of this colour previously reported Valdez & Mehrabian, 1994).
- H2 Image type would modulate discomfort and SSVEP amplitude, with stripe and bumps stimuli, with a concentration of energy around a particular spatial frequency, eliciting higher values than natural scenes (Fernandez & Wilkins, 2008).
- H3 Spatial frequency would interact with image type, exerting different effects on discomfort for stripes versus bumps (O'Hare & Hibbard, 2024).
- H4 Discomfort ratings and SSVEP amplitude would be positively correlated across conditions.

2. Methods

2.1. Participants

There were 21 participants aged between 18 and 43 years. Data from two participants were excluded, one due to incomplete data and one due to data corruption, leaving 19 participants for analysis (17 female, 1 non-binary). The mean age was 22.7 years (SD = 6.5).

The study was approved by the University of Stirling General University Ethics Panel (GUEP 2024 18703 14535). Participants were recruited from the general population, with recruitment materials explicitly encouraging individuals self-identifying as having sensory sensitivities to take part. Individuals with photosensitive epilepsy were excluded because of the use of flickering stimuli. Written informed consent was obtained from all participants prior to taking part.

2.1.1. Power considerations

Our target effect size was based on O'Hare and Hibbard (2024), who reported mean discomfort differences of about 0.8 Likert units between natural and artificial images. Power analysis suggested a required sample size of approximately 33–55 participants for 80% power, depending on the assumed within-participant variance. Given that SSVEP studies often use modest samples (typically 12–24 participants) because of their high signal-to-noise ratio and dense within-subject design (O'Hare, 2017), we aimed for an intermediate sample size.

2.2. Apparatus

The study was presented using an HP Z1 G9 computer with an Intel i7 processor and an NVIDIA GeForce RTX 3060 graphics card, running Windows 10. Stimuli were displayed on a 23-inch HP E23 G4 monitor with a resolution of 1920 × 1080 and a refresh rate of 60 Hz. Presentation was controlled using MATLAB 2023b and Psychtoolbox (Brainard et al., 2024; Kleiner et al., 2007). Images were 512 × 512 pixels and, at a viewing distance of 100 cm, subtended approximately 7.8°×7.8° of visual angle. One pixel subtended 0.9 arc min. Display luminance and chromaticity were measured using a Minolta CS-100 A chroma meter (Konica Minolta, Tokyo, Japan) by presenting a uniform image patch with the highest luminance value in the stimulus window.

EEG data were recorded using a Compumedics Neuroscan SynAmps2 system and SCAN 4.5 software (Compumedics Neuroscan, 2020) with a 64-channel electrode cap and 6 facial electrodes placed at the left and right mastoids, the outer canthi, and the left supra- and infraorbital sites. Data were acquired with a sampling rate of 1000 Hz. The EEG signal was bandpass filtered between 0.1 Hz and 100 Hz.

2.3. Materials

The Leiden Visual Sensitivity Scale (L-VISS) (Perenboom et al., 2018) is a 9-item self-report questionnaire designed to measure subjective visual sensitivity, including sensitivity to flicker, brightness, and high-contrast patterns (Brink et al., 2021). Each item is rated on a 4-point scale from 0 *(not at all)* to 3 *(very much)*, giving a total score between 0 and 27, with higher scores indicating greater visual discomfort.

2.4. Stimuli

All images were provided with consent from O'Hare and Hibbard (2024) and natural images were taken from the van Hateren and van der Schaaf (1998) image database, and included five greyscale photographs (image numbers 17, 28, 34, 47, and 129). Artificial stimuli included "bump" stimuli (filtered noise textures) created following the methods of Fernandez and Wilkins (2008). Briefly, this method involves first creating filtered noise patterns with a 1/f amplitude spectrum, thus creating noise images that have the second-order statistical properties of natural images. The second step is to create a filter (in this case a raised radial cosine filter) to increase the contrast amplitude at particular spatial frequencies. This has the effect of adding a "bump" to the otherwise 1/f amplitude spectrum. The location of the "bump" can be varied to create images with peaks in contrast amplitude at different spatial frequencies. In addition to the bump stimuli, there were five "stripe" stimuli comprising vertical sinusoidal gratings. These were generated at five spatial frequency levels; 0.70, 1.4, 2.8, 5.6 and 8.5 cycles per degree (cpd). Stimuli were windowed with a circular Gaussian mask comprising a central flat region of radius 3.9° and a soft edge defined by a Gaussian fall-off with standard deviation $\sigma = 0.26°$ of visual angle. Stimuli were allowed to vary in RMS contrast, to maintain natural variations in contrast. Each image was rendered in three colour conditions (grey, blue, red) by mapping contrast to brightness in HSV colour space. Coloured stimuli were created by assigning fixed hue values (blue = 0.6, red = 0.0) with constant saturation (0.6). Kruskal–Wallis tests showed that image type varied systematically in terms of RMS contrast (χ^2 (2) = 12.50, p = 0.002), but not spectral slope (χ^2 (2) = 0.27, p = 0.602) or fractal dimension (χ^2 (2) = 4.52, p = 0.104). Natural images showed the lowest RMS contrast, and stripes had the greatest RMS contrast values (see Fig. 1).

Table 1
Photometer measurements (luminance and chromaticity).

Condition	Luminance (Y)	x	y
Black	0.5	0.285	0.259
Maximum grey	27.9	0.318	0.350
Maximum blue	11.6	0.224	0.243
Maximum red	8.85	0.481	0.330

2.5. Procedure

Participants were seated in a sound-attenuated darkened room, approximately 100 cm from the display. Each trial began with a white fixation cross (1.7° of visual angle) presented on a mid-grey background for 500 ms, followed by stimulus presentation. Stimuli were shown for 20 s, flickering sinusoidally at 5 Hz with contrast modulated between peak and mid-grey. After each trial, participants rated their level of visual discomfort using a 7-point Likert scale, where 1 indicated *not at all uncomfortable* and 7 *very uncomfortable*. No guidance was provided on how to interpret discomfort, and no practice trials were given. A fixation cross was shown again following the response to ensure a brief pause before the next trial and to minimise carry-over effects. The experiment consisted of three counterbalanced blocks corresponding to each chromatic condition (grey, red, and blue), see Table 1 for luminance and chromaticity measurements. Within each block, participants viewed 15 images (five bumps, five stripes, five natural), each presented three times in randomised order, resulting in 45 trials per block and 135 trials in total. The ambient light in the room was therefore tinted by the display, and no specific adaptation period to this coloured ambient light was provided beyond the exposure during the experiment itself.

EEG pre-processing

EEG data were pre-processed using the EEGLAB toolbox (Delorme & Makeig, 2004) in MATLAB R2024b. Data were imported from `.cnt` files and electrode locations assigned according to the standard 10-5 system. Signals were resampled to 500 Hz, band-pass filtered between 0.1 and 40 Hz, and re-referenced to the average of all scalp electrodes, excluding ocular channels. Noisy channels were identified and removed using kurtosis thresholds. Continuous recordings were segmented into 20-second epochs time-locked to stimulus onset, then subdivided into nine consecutive 2 s segments per trial. Segments exceeding ±500 μV were automatically rejected. Independent component analysis (ICA) was performed to remove blink-related artefacts.

Spectral analysis

Spectral power was estimated using Welch's method, implemented via the `pwelch` function in MATLAB. For each 2-second segment, data were averaged across six occipital electrodes (OZ, O1, O2, POZ, PO3, PO4) to enhance signal-to-noise ratio. Power spectral density (PSD) was calculated using a Hamming window with an FFT length set to the next power of two relative to the segment length. Spectral values were converted to decibels, and power at 5 Hz, the frequency of the steady-state visual evoked potential (SSVEP), was extracted.

Power values at 5 Hz were averaged across segments for each observer, stimulus, and colour condition (blue, grey, red). Each trial was labelled according to observer ID, colour condition, and image

Fig. 1. Three representative stimuli (left "bump", middle "stripe", and right "natural" image) were extracted in one of each colour condition blue, red and grey respectively.

type (bumps, stripes, natural), producing a long-format dataset for subsequent statistical analysis. The Supplementary Information contains images showing the scalp topography and the spectra averaged over observers as an indication of data quality — the SSVEP peaks can clearly be seen.

3. Results

Relationship between neural and subjective discomfort (H4)

We examined whether variation in neural responses predicted variation in trial-by-trial Likert discomfort ratings. This was tested using a linear mixed-effects model with z-standardised SSVEP amplitude as a predictor of Likert discomfort ratings, and a random intercept for each participant. This approach allowed us to assess the association between neural and subjective measures across all trials while accounting for repeated observations within individuals.

$$\texttt{Lkt} \sim \texttt{zSSVEP} + (1 \mid \texttt{Observer}).$$

The zSSVEP predictor was obtained by standardising SSVEP amplitudes across all trials:

$$z = \frac{x - \bar{x}}{\sigma},$$

where $\bar{x}$ is the mean amplitude and σ the standard deviation. Positive values indicate above-average amplitudes; negative values indicate below-average amplitudes.

Consistent with H4, there was a significant positive association between zSSVEP and discomfort ratings, $b = 0.97$, $SE = 0.14$, $t(169) = 6.85$, $p < .001$, indicating that trials with higher neural responses tended to receive higher discomfort ratings. The model intercept, representing mean discomfort when SSVEP amplitude was at its mean ($z = 0$), was also significant, $b = 3.80$, $SE = 0.26$, $t(16.16) = 14.66$, $p < .001$, reflecting that all ratings were positive or zero.

Full factorial model with colour (H1) and image type (H2)

To test whether the association between SSVEP amplitude and discomfort varied by filter colour or image type, we fitted a linear mixed-effects model with zSSVEP, Colour, Image Type, and all interactions, with a random intercept for each participant:

$$\texttt{Lkt} \sim \texttt{zSSVEP} * \texttt{Colour} * \texttt{ImageType} + (1 \mid \texttt{Observer}).$$

Reference levels were grey (Colour) and bumps (Image Type), so the intercept corresponds to the estimated mean discomfort for grey bumps when zSSVEP = 0 (average amplitude). See Supplementary Information for the full table of fixed effects and Fig. 2 for scatterplots. The intercept was significant, $b = 2.71$, $SE = 0.18$, $t(153) = 14.86$, $p < .001$, representing the estimated mean discomfort rating for grey bumps when zSSVEP = 0.

Consistent with H1, blue screen filters were associated with significantly lower discomfort than grey ($b = -0.78$, $p < .001$), whereas red screen filters did not differ from grey ($p = .992$).

Consistent with H2, stripes ($b = 1.31$, $p < .001$) and natural images ($b = 2.21$, $p < .001$) elicited significantly higher discomfort than bumps.

The blue × natural interaction was significant ($b = 0.90$, $p = .007$), indicating a larger discomfort increase for natural images under blue screen filters relative to grey. This is a small effect and so not immediately apparent from the figure, but can be seen in the estimated marginal means (see Supplementary Information). The difference between blue natural images (4.92) and blue bump images (2.35) is 2.57, compared to the difference between grey natural (5.17) and grey bump (2.62) images, which is 2.55).

The main effect of zSSVEP in the reference condition (grey/bumps) was positive but non-significant ($p = .062$). A significant interaction between blue and zSSVEP ($b = -0.88$, $p = .002$) indicated that the neural–discomfort slope was less positive under blue than under grey filters. This shows that colour affected the association between neural activity and discomfort, with a weaker relationship (reduced slope relating discomfort and SSVEP) under the blue screen filter. All other two-way and three-way interactions with zSSVEP were non-significant ($p > .08$).

3.1. Spatial frequency and discomfort for flickering stimuli

To assess the effect of spatial frequency on visual discomfort (H3), we analysed Likert ratings from artificial stimuli (stripes and bumps), excluding natural images. For each image (collapsed across colour screen filters), we computed mean discomfort ratings across participants and plotted these as a function of spatial frequency, separately for each image type (see Fig. 3). Spatial frequency values were $\log_2$-transformed prior to modelling to linearise their relationship with discomfort.

In each linear mixed-effects model, discomfort ratings were predicted from the $\log_2$-transformed spatial frequency (in cycles per degree, CPD), with a random intercept for Observer to account for repeated measures:

$$\texttt{Lkt}_{\text{Stripe}} \sim \log_2(\texttt{CPD}) + (1 \mid \texttt{Observer}),$$

$$\texttt{Lkt}_{\text{Bump}} \sim \log_2(\texttt{CPD}) + (1 \mid \texttt{Observer}).$$

For stripe images, there was a significant negative relationship between spatial frequency and discomfort ratings ($\beta = -0.125$, $p < 0.001$), indicating that discomfort ratings tended to decrease as spatial frequency increased for our flickering stimuli.

In contrast, for bump images, spatial frequency was a significant positive predictor of discomfort ($\beta = 0.336$, $p < 0.001$), suggesting that discomfort increased with spatial frequency. These opposing trends highlight how broadband, structured image content modulates the influence of spatial frequency on visual discomfort. The higher ratings

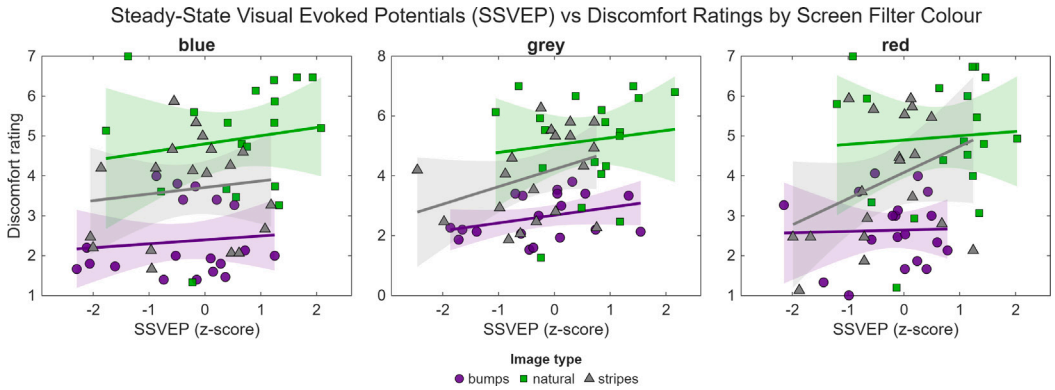

Fig. 2. Scatterplots of within-observer *z*-standardised SSVEP amplitude versus discomfort ratings, separated by screen filter colour (left: blue, centre: grey, right: red). Points represent individual trials and are coloured and shaped by image type (bumps, purple circles; natural images, green squares; stripes, grey triangles). Solid lines show the best-fitting linear regression for each image type, with shaded bands indicating the 95% confidence intervals. Steady-state visual evoked potential (SSVEP) amplitude values were standardised within each observer (by taking z-scores) across all trials. Discomfort ratings are shown on the original 1–7 Likert scale.

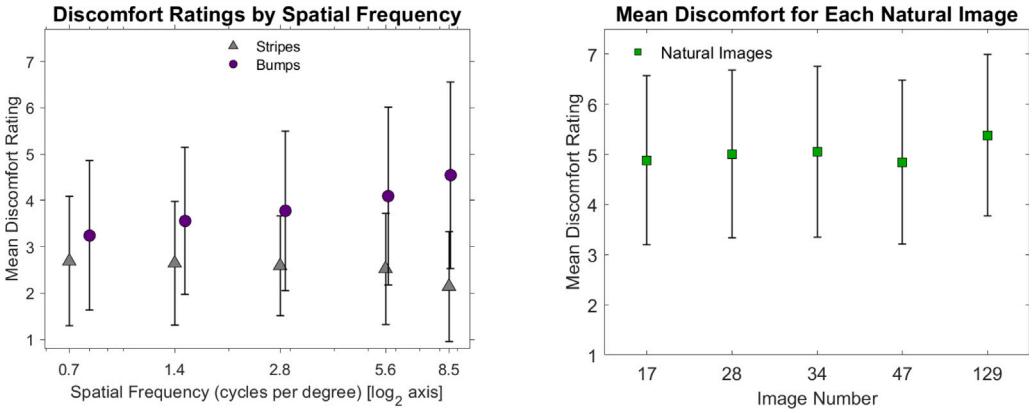

Fig. 3. Left: Mean discomfort ratings (error bars show ±1 standard deviation of the mean) for stripe (grey triangles) and bump (purple circles) images across spatial frequencies (cycles per degree, $\log_2$ scale). Each point represents one image, averaged across participants and screen filter conditions. Points on the figure have been jittered for clarity, but the spatial frequencies were the same for both. Ratings for bumps increase with spatial frequency, while ratings for stripes remain low and relatively flat. **Right**: Mean discomfort ratings for natural images (green squares) show low variability across individual scenes. Error bars show ±1 standard deviation of the mean.

of discomfort for bump images, in comparison with stripes, is consistent with the fact that they are dominated by low frequency components.

The distribution of discomfort ratings across spatial frequencies for stripe and bump stimuli is shown in the Supplementary Information.

4. Discussion

This study investigated whether a blue colour screen filter could reduce visual discomfort, and whether this effect was reflected in a neural marker, the steady-state visual evoked potential (SSVEP).

4.1. Contribution of colour

H1 stated that blue and red screen filters would reduce discomfort ratings and SSVEP amplitudes relative to greyscale. This was partly supported: discomfort ratings were lower with the blue screen filter than with grey, but the effect was modest and varied across image types. There was no reliable reduction in SSVEP amplitude for either colour screen filter. Our results add to the mixed evidence on colour screen filters and visual discomfort. Blue filters produced a small reduction in discomfort ratings, consistent with reports of tinted lens benefits in migraine and visual stress (Good et al., 1991; Hoggan et al., 2016; Huang et al., 2011). At the same time, we found no reliable effect on SSVEP amplitude, in line with reviews that report weak or inconsistent neural evidence (Griffiths et al., 2016; O'Connor, 2011).

Our initial prediction was that either colour (red or blue) might reduce discomfort, with blue providing the greatest effect. This was based on testing a colour-neutral prediction that providing any filter might reduce discomfort. However, it might also have been predicted from previous empirical results that red filters might increase discomfort, since red light is typically more epileptogenic in epilepsy patients (Fisher et al., 2022; Gasparini et al., 2025; Parra et al., 2007) and has been associated with higher levels of discomfort (Haigh et al., 2013, 2019; Juricevic et al., 2010; Lindquist et al., 2021; Yoshimoto et al., 2025).

4.1.1. Discomfort from images and inefficient coding

H2 predicted that artificial images (stripes and bumps) would produce greater discomfort than natural images. This was not supported: both artificial image types were in fact rated as less uncomfortable than natural images on average. Because the artificial images tended to have higher RMS contrast than the natural images, this provides further support that discomfort is not accounted for by contrast alone (O'Hare & Hibbard, 2011). While some natural images received high discomfort ratings, this is not necessarily at odds with the idea that the visual system is adapted to natural statistics (Field, 1987; Simoncelli & Olshausen, 2001). Given that the natural images had lower RMS contrast, it is possible that some discomfort arose from lack of image clarity

(O'Hare, Foubister et al., 2012). It should also be noted that the natural images will have been dominated by low spatial frequency components, and that the combination of spatial and temporal frequency properties will have jointly influenced discomfort (Hibbard, Asher et al., 2026).

H3 predicted that spatial frequency would affect discomfort differently for stripes and bumps. This was supported: discomfort decreased with increasing spatial frequency for stripes and increased for bumps. Our spatial frequency results also align with past research showing that discomfort peaks at mid to high frequencies for striped patterns (O'Hare & Hibbard, 2011; Penacchio & Wilkins, 2015; Wilkins et al., 1984). We extend this by showing that the effect depends on image type: bumps became more uncomfortable at higher frequencies, while stripes became less uncomfortable (Fernandez & Wilkins, 2008; Hibbard & O'Hare, 2015; Juricevic et al., 2010). The stronger effect for bumps may reflect their greater structural complexity and the dominance of low spatial frequencies, which place higher demands on processing (Hibbard et al., 2023).

Given the opposite trends for stripes and bumps, these findings suggest that discomfort is not determined by spatial frequency peaks alone. Higher spatial frequencies reduced discomfort for stripes but increased it for bumps, suggesting that the effect of spatial frequency may depend on how contrast is arranged across the image.

Importantly, our results are for flickering rather than static stimuli, which is a necessary factor in shaping the spatial frequency tuning of neural responses (Tyler et al., 1978). In addition, for flickering stimuli, discomfort may be more closely tied to the low spatial frequencies that dominate natural images, as suggested by the tuning of discomfort for sinusoidal gratings.

4.2. Relationship between discomfort and SSVEP responses

H4 predicted that discomfort ratings and SSVEP amplitude would be positively related across conditions. This was partially supported: across trials, higher amplitudes predicted higher discomfort ratings, suggesting that neural responses reflect subjective experience. The association between discomfort and SSVEP amplitude replicates earlier findings that uncomfortable patterns drive stronger neural responses (Gentile & Aguirre, 2020; Haigh et al., 2013; O'Hare, 2017). The predicted link between discomfort ratings and SSVEP responses can be seen in Fig. 2 for the greyscale condition, where there is a positive relationship between z-scored SSVEP responses and discomfort ratings. There is also an overall positive relationship for the red coloured images, and particularly in the case of the stripes. However, for the blue screen filter the relationship appears flatter. Moreover, the difference between grey and red is not statistically significant, whereas there is a statistically significant difference between grey and blue, indicating that this relationship disappeared under the blue screen filter. Therefore, the relationship between discomfort and SSVEP weakened under the blue screen filter. This indicates that colour changed how neural activity translated into discomfort in a way that did not depend on change in mean SSVEP amplitude.

Studies have shown that low-level image statistics such as deviations from the 1/f amplitude spectrum contribute to visual discomfort (Fernandez & Wilkins, 2008; Juricevic et al., 2010), forming the basis for the idea of inefficient processing as a cause of visual discomfort. However, low-level image statistics are unlikely to be the sole contributors, for example, higher-order statistical properties such as edge information also relate to discomfort, including edge orientation (Burke & Longo, 2026; O'Hare & Hibbard, 2024), blurring (O'Hare & Hibbard, 2013), and one-dimensional flicker (Yoshimoto et al., 2017).

It might appear that the addition of the coloured filter, which does not alter low-level image spatial statistics, would challenge this theory. However, this is not necessarily the case, as inefficient processing can still account for some aspects of what makes an image uncomfortable. The question of why colour would make otherwise uncomfortable images more comfortable to view remains unresolved and is a major source of controversy in the literature on coloured overlays and spectacles. One fMRI study has shown that, in people with migraine, coloured lenses reduce cortical activity throughout the visual cortex, with the greatest reduction in higher-order areas (Huang et al., 2011). As we did not target later visual processing areas, this issue lies beyond the scope of the present study and remains a question for future research.

4.2.1. Individual variation and E–I imbalance

Random intercepts for Observer captured baseline differences in discomfort ratings, revealing stable individual variability. Such variability is consistent with previous findings that visual discomfort is shaped by stable, trait-like differences in sensory sensitivity (Fernandez & Wilkins, 2008; Wilkins et al., 1984). In the present study, this likely reflects individual thresholds for discomfort rather than systematic effects of the experimental manipulations. Although on average higher SSVEP amplitudes predicted higher discomfort, individual participants varied in how strongly neural responses translated into discomfort ratings. These results highlight the importance of accounting for individual profiles when evaluating potential interventions: benefits from colour screen filters or other approaches may depend on tailoring strategies to individual differences (Huang et al., 2011; Wilkins & Neary, 1991).

As outlined in the Introduction, the E–I imbalance account proposes that discomfort arises when the balance between cortical excitatory and inhibitory processes is disrupted, leading to heightened neural responsiveness to certain visual patterns (Huang et al., 2011). This mechanistic account has been proposed in both migraine and autism, with evidence compatible with increased cortical excitability and altered inhibition (Demarquay & Mauguière, 2016; Dunn & Jones, 2020; O'Hare, Tarasi et al., 2023), although it must be noted that this idea has been challenged in recent research (Sumner et al., 2026; Ward et al., 2025). The E-I imbalance account would make predictions about the traits of observers, rather than predictions about specific images. Specifically, previous researchers used gamma oscillations to index E-I imbalance and found there to be no relationship with an individual's trait discomfort (Sumner et al., 2026). In the current study, we focussed on the predictions about specific images, rather than traits, and so do not address E-I imbalance directly. Although we did find stable traits (based on the L-VISS scale) and these related to mean instantaneous discomfort ratings (see Supplementary Information), we do not have suitable metrics such as gamma band oscillations or direct measures of neurotransmitter concentrations to link this to E-I imbalance in terms of brain chemistry.

4.3. Limitations

We did not attempt to match stimuli for low-level image properties, as our focus was on colour screen filtering and the neural–subjective relationship across a broad range of image types. Low-level image properties are important to discomfort judgements, however it is not possible to match them all as this will change the nature of the image. For example edge information, which is important for discomfort judgements (O'Hare & Hibbard, 2024), contains the semantic information of the image. In previous work efforts have been made to match for contrast, whether physical or perceived (O'Hare et al., 2021). It has been shown that contrast effects cannot account for discomfort judgements (O'Hare & Hibbard, 2011), but contrast effects can dominate the SSVEP responses (O'Hare & Hibbard, 2024). In the current study, we show that there are some interactions between discomfort, image type and the neural response. However, as we chose not to match for RMS contrast, we do not interpret these small interactions conclusively. Nevertheless, overall image contrast cannot explain the effects of colour in our study, since differences in contrast between grey and red stimuli were not reflected in differences in discomfort.

It is unknown what the perceived contrast of the images would be, following filtering. Differences in overall luminance across filter conditions will have affected RMS contrast. More importantly, perceived

luminance varies at different contrast pedestals and there is evidence of an interaction between luminance and chromatic systems (Shooner & Mullen, 2020). Moreover, discrimination thresholds for colour stimuli vary for individual observers, even for white-point settings (Bosten et al., 2015). In the current study, the potential impact of this is out of scope, as we did not measure perceived contrast for each observer.

Recruitment was targeted towards individuals who self-reported heightened sensory sensitivity, consistent with evidence that sensory sensitivity varies widely in the population and may be more pronounced in certain groups (Evans & Stevenson, 2008; O'Hare & Hibbard, 2011). While this approach increased the likelihood of detecting relevant effects, it may also have introduced self-selection bias and restricted the ability to generalise the results as representative of the population average. Variability in how participants interpret and report sensory sensitivity could limit comparability across individuals and reduce the generalisability of our findings. Nevertheless, the key effects of spatial frequency and image type were consistent across participants, and the small, inconsistent differences between colour screen filter conditions suggest the overall pattern of results would likely have been similar in a more broadly defined sample.

Our sample size was 21, with 19 included in the analysis. Given that one of our aims was to investigate individual differences, this is not a broad sample of the population, and so the interpretation of our results is limited by this. However, although power analysis suggested a larger sample for detecting overall effects, this is based on assumed within-participant variation. Despite the small sample, data quality is reasonable (see Supplementary Information). Additionally, linear mixed effects models have advantages over other methods for analysing data from smaller samples (Muth et al., 2016) and each participant provided a high volume of trial-level information.

The scope of colour screen filters tested was limited to blue and red, constraining conclusions about the wider applicability of colour-based interventions. However, in the SSVEP data, no reliable differences were observed between colour conditions, suggesting that broadening the range of screen filters may not necessarily yield strong neural effects.

Finally, the colour manipulations were applied digitally to the stimuli rather than using physical overlays or tinted lenses. This approach provided precise manipulation of luminance, chromaticity, and timing, ensuring consistent application across conditions and minimising variability. The ambient light in the room would have been coloured, which might have resulted in adaptation effects on both the behavioural and the neural responses. It has been shown that SSVEP responses to colour show adaptation effects in a way that SSVEP responses to luminance do not (Zhang et al., 2023). Here, the authors suggested that stimulation periods of 20 s or less would not incur strong adaptation effects of coloured stimuli in the SSVEP responses (Zhang et al., 2023). However, there was no specific adaptation period aside from the presentation of the stimuli, and so this is a key difference between using digital screen filters and spectacles, as spectacles would be worn for longer durations. Moreover, there are additional reasons why digital screen filters may not fully replicate the perceptual or physiological effects of wearing tinted lenses in everyday contexts — as well as adaptation to the colour, they will also affect peripheral vision, and viewing behaviour (Wilkins et al., 2004). As such, the neural and subjective responses reported here may differ from those experienced during real-world use of filters, and be more directly relevant to the use of device-screen tints or physical overlays. It is also important to note that SSVEPs cannot directly measure excitatory or inhibitory processes, only providing an indirect index of cortical activity.

4.4. Conclusion

Our findings suggest that colour screen filters may not reduce early visual cortical responses to uncomfortable patterns but can change how these responses are experienced. Blue screen filters lowered discomfort without reducing SSVEP amplitude, and the usual positive association between SSVEP amplitude and discomfort was weaker under blue screen filtering. This dissociation suggests that blue screen filters may not reduce cortical hyperexcitability in the early visual areas, but may change how neural activity is experienced as discomfort. Such effects may be relevant for visual stress interventions in conditions like migraine or autism, where visual discomfort is common. Discomfort also varied with image type and spatial frequency: ratings increased with frequency for bump textures but remained stable or decreased for stripes. These patterns are consistent with accounts linking discomfort to inefficient coding and altered excitation–inhibition balance (Gentile & Aguirre, 2020; O'Hare, 2017; Penacchio & Wilkins, 2015).

Ethics declaration

Written informed consent to take part in the study and to publish the article has been obtained from all participants or their legal representatives. The privacy rights of participants have been observed.

This study was performed in compliance with relevant laws, regulatory frameworks and guidelines where the research took place. This study was approved by the General University Ethics Panel. (Approval No. GUEP 2024 18703 14535)

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CRediT authorship contribution statement

Caelan Dow: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jordi M. Asher:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Paul B. Hibbard:** Writing – review & editing, Writing – original draft, Supervision. **Caitlin Evans:** Resources, Project administration, Investigation, Data curation. **Louise O'Hare:** Writing – review & editing, Writing – original draft, Software, Resources, Methodology.

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.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.visres.2026.108897.

Data availability

The preprocessed datasets and supporting materials associated with this research are available on the Open Science Framework (OSF) at https://osf.io/jndsx/.

References

Aron, E. N., Aron, A., & Jagiellowicz, J. (2012). Sensory processing sensitivity. *Personality and Social Psychology Review*, *16*(3), 262–282. http://dx.doi.org/10.1177/1088868311434213.

Attneave, F. (1954). Some informational aspects of visual perception. *Psychological Review*, *61*(3), 183–193. http://dx.doi.org/10.1037/h0054663.

Barlow, H. B., et al. (1961). Possible principles underlying the transformation of sensory messages. *Sensory Communication*, *1*(01), 217–233.

BarNir, A., Shaked, H., Elad, S., & Tosta, S. (2023). Evidence for overlapping visual processing difficulties in adult ADHD and visual stress. *Perceptual and Motor Skills*, *130*(5), 2087–2105.

Bosten, J., Beer, R., & MacLeod, D. (2015). What is white? *Journal of Vision*, *15*(16), 5–5.

Boyce, P. R., & Wilkins, A. (2018). Visual discomfort indoors. *Lighting Research & Technology*, *50*(1), 98–114.

Brainard, D. H., Kleiner, M., Pelli, D. G., Ingling, A., et al. (2024). Psychtoolbox: Software for visual psychophysics and neuroscience experiments. *Journal of Vision*, *24*(2), 1–17. http://dx.doi.org/10.1167/jov.24.2.1.

Braithwaite, J. J., Marchant, R., Takahashi, C., Dewe, H., & Watson, D. G. (2015). The cortical hyperexcitability index (CHi): A new measure for quantifying correlates of visually driven cortical hyperexcitability. *Cognitive Neuropsychiatry*, *20*(4), 330–348.

Brinciotti, M., Wilkins, A. J., Penacchio, O., & Matricardi, M. (2021). Pattern-sensitive patients with epilepsy use uncomfortable visual stimuli to self-induce seizures. *Epilepsy & Behavior*, *122*, Article 108189.

Brink, A. F. T., Proulx, M. J., & Bultitude, J. H. (2021). Validation of the leiden visual sensitivity scale and visual discomfort scale in chronic pain conditions. *Perception*, *50*(5), 399–417. http://dx.doi.org/10.1177/03010066211005327.

Burke, B., & Longo, M. (2026). An oblique effect for visual comfort. *Vision Research*, unpublished manuscript.

Chen, Q., Deister, C. A., Gao, X., Guo, B., Lynn-Jones, T., Chen, N., Wells, M. F., Liu, R., Goard, M. J., Dimidschstein, J., Feng, S., Shi, Y., Liao, W., Lu, Z., Fishell, G., Moore, C. I., & Feng, G. (2020). Dysfunction of cortical GABAergic neurons leads to sensory hyper-reactivity in a Shank3 mouse model of ASD. *Nature Neuroscience*, *23*(4), 520–532. http://dx.doi.org/10.1038/s41593-020-0598-6.

Compumedics Neuroscan (2020). *SynAmps2 and SCAN 4.5: EEG and ERP recording system*. Charlotte, NC, USA: Compumedics Ltd., Available from: https://compumedicsneuroscan.com.

Conlon, E., Lovegrove, W., Barker, S., & Chekaluk, E. (2001). Visual discomfort: The influence of spatial frequency. *Perception*, *30*(5), 571–581.

Conlon, E. G., Lovegrove, W. J., Chekaluk, E., & Pattison, P. E. (1999). Measuring visual discomfort. *Visual Cognition*, *6*(6), 637–663.

Costa-López, B., Ferrer-Cascales, R., Ruiz-Robledillo, N., Albaladejo-Blázquez, N., & Baryła-Matejczuk, M. (2021). Relationship between sensory processing and quality of life: A systematic review. *Journal of Clinical Medicine*, *10*(17), 3961. http://dx.doi.org/10.3390/jcm10173961.

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*(1), 9–21. http://dx.doi.org/10.1016/j.jneumeth.2003.10.009.

Demarquay, G., & Mauguière, F. (2016). Central nervous system underpinnings of sensory hypersensitivity in migraine: Insights from neuroimaging and electrophysiological studies. *Headache: The Journal of Head and Face Pain*, *56*(9), 1418–1438.

Dunn, S., & Jones, M. (2020). Binocular rivalry dynamics associated with high levels of self-reported autistic traits suggest an imbalance of cortical excitation and inhibition. *Behavioural Brain Research*, *388*, Article 112603. http://dx.doi.org/10.1016/j.bbr.2020.112603.

Evans, B., & Stevenson, S. (2008). The pattern glare test: A review and determination of normative values. *Ophthalmic & Physiological Optics*, *28*(4), 295–309.

Fernandez, D., & Wilkins, A. J. (2008). Uncomfortable images in art and nature. *Perception*, *37*(7), 1098–1113. http://dx.doi.org/10.1068/p5814.

Field, D. J. (1987). Relations between the statistics of natural images and the response properties of cortical cells. *Journal of the Optical Society of America A*, *4*(12), 2379–2394.

Field, D. J. (1994). What is the goal of sensory coding? *Neural Computation*, *6*(4), 559–601.

Fisher, R. S., Acharya, J. N., Baumer, F. M., French, J. A., Parisi, P., Solodar, J. H., Szaflarski, J. P., Thio, L. L., Tolchin, B., Wilkins, A. J., et al. (2022). Visually sensitive seizures: An updated review by the Epilepsy foundation. *Epilepsia*, *63*(4), 739–768.

Franklin, A., Sowden, P., Burley, R., Notman, L., & Alder, E. (2008). Color perception in children with autism. *Journal of Autism and Developmental Disorders*, *38*(10), 1837–1847.

Gasparini, S., Dainelli, A., Piras, F., Balestrini, S., & Guerrini, R. (2025). Red-light flashing pens and seizures in children. *Developmental Medicine & Child Neurology*.

Gentile, C. P., & Aguirre, G. K. (2020). A neural correlate of visual discomfort from flicker. *Journal of Vision*, *20*(7), 11. http://dx.doi.org/10.1167/jov.20.7.11.

Good, P., Taylor, R., & Mortimer, M. (1991). The use of tinted glasses in childhood migraine. *Headache: The Journal of Head and Face Pain*, *31*(8), 533–536.

Greven, C., Trupp, M. D., Homberg, J. R., & Slagter, H. (2024). Sensory processing sensitivity: Theory, evidence and directions. http://dx.doi.org/10.31234/osf.io/wkdhg, Preprint.

Griffiths, P. G., Taylor, R. H., Henderson, L. M., & Barrett, B. T. (2016). The effect of coloured overlays and lenses on reading: A systematic review of the literature. *Ophthalmic & Physiological Optics*, *36*(5), 519–544.

Haigh, S. M., Barningham, L., Berntsen, M., Coutts, L. V., Hobbs, E. S., Irabor, J., Lever, E. M., Tang, P., & Wilkins, A. J. (2013). Discomfort and the cortical haemodynamic response to coloured gratings. *Vision Research*, *89*, 47–53.

Haigh, S. M., Chamanzar, A., Grover, P., & Behrmann, M. (2019). Cortical hyperexcitability in migraine in response to chromatic patterns. *Headache: The Journal of Head and Face Pain*, *59*(10), 1773–1787.

Haigh, S. M., Cooper, N. R., & Wilkins, A. (2018). Chromaticity separation and the alpha response. *Neuropsychologia*, *108*, 1–5.

Harkin, D. L., Little, J.-A., & McCullough, S. J. (2024). Reading; through the eyes of a university student: A double-masked randomised placebo-controlled cross-over protocol investigating coloured spectacle lens efficacy in adults with visual stress. http://dx.doi.org/10.1101/2024.08.18.24312188, MedRxiv (Cold Spring Harbor Laboratory).

Harle, D. E., Shepherd, A. J., & Evans, B. J. (2006). Visual stimuli are common triggers of migraine and are associated with pattern glare. *Headache: The Journal of Head and Face Pain*, *46*(9), 1431–1440.

van Hateren, J., & van der Schaaf, A. (1998). Independent component filters of natural images compared with simple cells in primary visual cortex. *Proceedings of the Royal Society B*, *265*, 359–366.

Hibbard, P. B., Allen, P., Asher, J. M., Batey, K., Burke, B., Braithwaite, J. J., Cole, G. G., Dow, C., Evans, B. J., Franklin, A., et al. (2026). A cerebral basis for visual discomfort and visual stress. *Vision*, *10*(2), 34.

Hibbard, P. B., Asher, J. M., O'Hare, L., Evans, C., & Dow, C. (2026). Visual discomfort for flickering sinusoids is not predicted by the spatio-temporal contrast sensitivity function. *Vision Research*, *238*, Article 108720.

Hibbard, P. B., Goutcher, R., Hornsey, R. L., Hunter, D. W., & Scarfe, P. (2023). Luminance contrast provides metric depth information. *Royal Society Open Science*, *10*(2), http://dx.doi.org/10.1098/rsos.220567.

Hibbard, P. B., & O'Hare, L. (2015). Uncomfortable images produce non-sparse responses in a model of primary visual cortex. *Royal Society Open Science*, *2*(2), Article 140535. http://dx.doi.org/10.1098/rsos.140535.

Hoggan, R. N., Subhash, A., Blair, S., Digre, K. B., Baggaley, S. K., Gordon, J., Brennan, K., Warner, J. E., Crum, A. V., & Katz, B. J. (2016). Thin-film optical notch filter spectacle coatings for the treatment of migraine and photophobia. *Journal of Clinical Neuroscience*, *28*, 71–76.

Huang, J., Zong, X., Wilkins, A., Jenkins, B., Bozoki, A., & Cao, Y. (2011). fMRI evidence that precision ophthalmic tints reduce cortical hyperactivation in migraine. *Cephalalgia*, *31*(8), 925–936. http://dx.doi.org/10.1177/0333102411409076.

Jacobs, K. W., & Hustmyer, F. E., Jr. (1974). Effects of four psychological primary colors on GSR, heart rate and respiration rate. *Perceptual and Motor Skills*, *38*(3), 763–766.

Juricevic, I., Land, L., Wilkins, A., & Webster, M. A. (2010). Visual discomfort and natural image statistics. *Perception*, *39*(7), 884–899. http://dx.doi.org/10.1068/p6656.

Kleiner, M., Brainard, D., Pelli, D., Ingling, A., Murray, R., & Broussard, C. (2007). What's new in psychtoolbox-3. *Perception*, *36*(14), 1–16.

Kurczewska, E., Ferensztajn-Rochowiak, E., Rybakowski, J., & Rybakowski, F. (2024). Sensory processing sensitivity as a trait of temperament - evolutionary, sociocultural, biological context and relation to mental disorders. *Psychiatria Polska*, *58*(2), 249–264. http://dx.doi.org/10.12740/pp/160301.

Lane, S. J., & Reynolds, S. (2019). Sensory over-responsivity as an added dimension in ADHD. *Frontiers in Integrative Neuroscience*, *13*, http://dx.doi.org/10.3389/fnint.2019.00040.

Le, A. T., Payne, J., Clarke, C., Kelly, M. A., Prudenziati, F., Armsby, E., Penacchio, O., & Wilkins, A. J. (2017). Discomfort from urban scenes: Metabolic consequences. *Landscape and Urban Planning*, *160*, 61–68.

Lévêque, Y., Masson, R., Fornoni, L., Moulin, A., Bidet-Caulet, A., Caclin, A., & Demarquay, G. (2020). Self-perceived attention difficulties are associated with sensory hypersensitivity in migraine. *Revue Neurologique*, *176*(10), 829–838. http://dx.doi.org/10.1016/j.neurol.2020.01.360.

Lindquist, L. C., McIntire, G. R., & Haigh, S. M. (2021). The effects of visual discomfort and chromaticity separation on neural processing during a visual task. *Vision Research*, *182*, 27–35. http://dx.doi.org/10.1016/j.visres.2021.01.007, URL: https://www.sciencedirect.com/science/article/pii/S0042698921000249.

Ludlow, A. K., Heaton, P., Hill, E., & Franklin, A. (2014). Color obsessions and phobias in autism spectrum disorders: The case of JG. *Neurocase*, *20*(3), 296–306.

MacLennan, K., Woolley, C., Andsensory, E., Heasman, B., Starns, J., George, B., & Manning, C. (2023). "It is a big spider web of things": Sensory experiences of autistic adults in public spaces. *Autism in Adulthood*, http://dx.doi.org/10.1089/aut.2022.0024.

Manyukhina, V. O., Rostovtseva, E. N., Prokofyev, A. O., Obukhova, T. S., Schneiderman, J. F., Stroganova, T. A., & Orekhova, E. V. (2021). Visual gamma oscillations predict sensory sensitivity in females as they do in males. *Scientific Reports*, *11*(1), 12013.

Martin, R., & Wilkins, J. (2022). Creating visually appropriate classroom environments for students with autism spectrum disorder. *Intervention in School and Clinic*, *57*(3), 176–181.

Maule, J., Stanworth, K., Pellicano, E., & Franklin, A. (2017). Ensemble perception of color in autistic adults. *Autism Research*, *10*(5), 839–851.

Ming En, L., Heng Yii Sern, C., Abdul Aziz, Z. B., & Jing Jing, L. (2026). Architectural colour and lighting strategies for autism-friendly physical learning environment in Malaysia. *Journal of Asian Architecture and Building Engineering*, 1–15.

Muth, C., Bales, K. L., Hinde, K., Maninger, N., Mendoza, S. P., & Ferrer, E. (2016). Alternative models for small samples in psychological research: Applying linear mixed effects models and generalized estimating equations to repeated measures data. *Educational and Psychological Measurement*, *76*(1), 64–87.

Nair, A. S., Priya, R. S., Rajagopal, P., Pradeepa, C., Senthil, R., Dhanalakshmi, S., Lai, K. W., Wu, X., & Zuo, X. (2022). A case study on the effect of light and colors in the built environment on autistic children's behavior. *Frontiers in Psychiatry*, *13*, http://dx.doi.org/10.3389/fpsyt.2022.1042641.

O'Connor, Z. (2011). Colour psychology and colour therapy: Caveat emptor. *Color Research & Application*, *36*(3), 229–234.

O'Hare, L. (2017). Steady-state VEP responses to uncomfortable stimuli. *European Journal of Neuroscience*, *45*(3), 410–422.

O'Hare, L., Foubister, C., Hibbard, P. B., Day, P., Colville, J., & Rohan, C. (2012). The effect of luminance and contrast on visual discomfort and clarity in display screen. In *Proc. predicting perceptions: 3rd int. conf. appearance* (pp. 142–144).

O'Hare, L., Goodwin, P., & Sharman, R. J. (2023). The relationship between visual discomfort and cortical excitability in cone-opponent stimuli. *Brain Research*, *1798*, Article 148142.

O'Hare, L., & Hibbard, P. B. (2011). Spatial frequency and visual discomfort. *Vision Research*, *51*(15), 1767–1777.

O'Hare, L., & Hibbard, P. B. (2013). Visual discomfort and blur. *Journal of Vision*, *13*(5), 7–7.

O'Hare, L., & Hibbard, P. B. (2024). Support for the efficient coding account of visual discomfort. *Visual Neuroscience*, *41*, E008.

O'Hare, L., Hird, E., & Whybrow, M. (2021). Steady-state visual evoked potential responses predict visual discomfort judgements. *European Journal of Neuroscience*, *54*(10), 7575–7598. http://dx.doi.org/10.1111/ejn.15492.

O'Hare, L., Tarasi, L., Asher, J. M., Hibbard, P. B., & Romei, V. (2023). Excitation-inhibition imbalance in migraine: From neurotransmitters to brain oscillations. *International Journal of Molecular Sciences*, *24*(12), 10093. http://dx.doi.org/10.3390/ijms241210093.

Olshausen, B. A., & Field, D. J. (2004). Sparse coding of sensory inputs. *Current Opinion in Neurobiology*, *14*(4), 481–487.

Olszewska-Guizzo, A., Sia, A., Fogel, A., & Ho, R. (2022). Features of urban green spaces associated with positive emotions, mindfulness and relaxation. *Scientific Reports*, *12*(1), http://dx.doi.org/10.1038/s41598-022-24637-0.

Parra, J., Lopes da Silva, F. H., Stroink, H., & Kalitzin, S. (2007). Is colour modulation an independent factor in human visual photosensitivity? *Brain*, *130*(6), 1679–1689.

Penacchio, O., Otazu, X., Wilkins, A. J., & Haigh, S. M. (2023). A mechanistic account of visual discomfort. *Frontiers in Neuroscience*, *17*, http://dx.doi.org/10.3389/fnins.2023.1200661.

Penacchio, O., & Wilkins, A. J. (2015). Visual discomfort and the spatial distribution of Fourier energy. *Vision Research*, *108*, 1–7. http://dx.doi.org/10.1016/j.visres.2014.12.013.

Pence, S. T., Wagoner, R., & St Peter, C. C. (2019). Blue light covers increase stereotypy and decrease on-task behavior for students with autism. *Behavior Analysis in Practice*, *12*(3), 632–636. http://dx.doi.org/10.1007/s40617-018-00321-6.

Perenboom, M. J., Najafabadi, A. H. Z., Zielman, R., Carpay, J. A., & Ferrari, M. D. (2018). Quantifying visual allodynia across migraine subtypes: The Leiden visual sensitivity scale. *Pain*, *159*(11), 2375–2382.

Pfeiffer, B., Braun, K., Kinnealey, M., Matczak, M. D., & Polatajko, H. (2017). Environmental factors impacting work satisfaction and performance for adults with autism spectrum disorders. *Journal of Vocational Rehabilitation*, *47*(1), 1–12. http://dx.doi.org/10.3233/jvr-170878.

Powell, G., Penacchio, O., Derry-Sumner, H., Rushton, S. K., Rajenderkumar, D., & Sumner, P. (2022). Visual stress responses to static images are associated with symptoms of persistent postural perceptual dizziness (PPPD). *Journal of Vestibular Research*, *32*(1), 69–78.

Price, A., Sumner, P., & Powell, G. (2025). Understanding the subtypes of visual hypersensitivity: Four coherent factors and their measurement with the cardiff hypersensitivity scale (CHYPS). *Vision Research*, *233*, Article 108610.

Ranford, J., MacLean, J., Alluri, P. R., Comeau, O., Godena, E., LaFrance, W. C., Hunt, A., Stephen, C. D., & Perez, D. L. (2020). Sensory processing difficulties in functional neurological disorder: A possible predisposing vulnerability? *Psychosomatics*, *61*(4), 343–352. http://dx.doi.org/10.1016/j.psym.2020.02.003.

Robertson, C. E., & Baron-Cohen, S. (2017). Sensory perception in autism. *Nature Reviews. Neuroscience*, *18*(11), 671–684. http://dx.doi.org/10.1038/nrn.2017.112.

Robertson, A. E., & Simmons, D. R. (2013). The relationship between sensory sensitivity and autistic traits in the general population. *Journal of Autism and Developmental Disorders*, *43*(4), 775–784. http://dx.doi.org/10.1007/s10803-012-1608-7.

Robertson, A. E., & Simmons, D. R. (2019). Glasgow sensory questionnaire (GSQ). In *Encyclopedia of autism spectrum disorders* (pp. 1–3). Springer.

Rubenstein, J. L. R., & Merzenich, M. M. (2003). Model of autism: Increased ratio of excitation/inhibition in key neural systems. *Genes Brain & Behavior*, *2*(5), 255–267. http://dx.doi.org/10.1034/j.1601-183x.2003.00037.x.

Schoen, S. A. (2009). Physiological and behavioral differences in sensory processing: A comparison of children with autism spectrum disorder and sensory processing disorder. *Frontiers in Integrative Neuroscience*, *3*, http://dx.doi.org/10.3389/neuro.07.029.2009.

Schwarz, J., Lizarazu, M., Lallier, M., & Klimovich-Gray, A. (2024). Phonological deficits in dyslexia impede lexical processing of spoken words: Linking behavioural and MEG data. *Cortex*, *171*, 204–222.

Shepherd, A. J., Hine, T. J., & Beaumont, H. M. (2013). Color and spatial frequency are related to visual pattern sensitivity in migraine. *Headache: The Journal of Head and Face Pain*, *53*(7), 1087–1103.

Shooner, C., & Mullen, K. T. (2020). Enhanced luminance sensitivity on color and luminance pedestals: Threshold measurements and a model of parvocellular luminance processing. *Journal of Vision*, *20*(6), 12–12.

Simoncelli, E. P., & Olshausen, B. A. (2001). Natural image statistics and neural representation. *Annual Review of Neuroscience*, *24*(1), 1193–1216.

Singh, S., Keller, P. R., Busija, L., McMillan, P., Makrai, E., Lawrenson, J. G., Hull, C. C., & Downie, L. E. (2023). Blue-light filtering spectacle lenses for visual performance, sleep, and macular health in adults. *Cochrane Database of Systematic Reviews*, (8).

Sinno, Z., & Bovik, A. C. (2018). Predicting 3D visual discomfort using natural scene statistics and a binocular model. *Applications of Digital Image Processing XLI*, *10752*, 148–159. http://dx.doi.org/10.1117/12.2320902.

Sohal, V. S., & Rubenstein, J. L. R. (2019). Excitation-inhibition balance as a framework for investigating mechanisms in neuropsychiatric disorders. *Molecular Psychiatry*, *24*(9), 1248–1257. http://dx.doi.org/10.1038/s41380-019-0426-0.

Sturgill, J. F., & Isaacson, J. S. (2015). Somatostatin cells regulate sensory response fidelity via subtractive inhibition in olfactory cortex. *Nature Neuroscience*, *18*(4), 531–535. http://dx.doi.org/10.1038/nn.3971.

Sumner, P., Powell, G., Price, A., Thomas, H., Reed, L. S., Perry, G., Hedge, C., & Singh, K. D. (2026). Sensory sensitivity and visual discomfort are not associated with altered gamma oscillations; A test of the excitation-inhibition hypothesis. *Imaging Neuroscience*.

Takarae, Y., & Sweeney, J. (2017). Neural hyperexcitability in autism spectrum disorders. *Brain Sciences*, *7*(10), 129. http://dx.doi.org/10.3390/brainsci7100129.

Tavassoli, T., Miller, L. J., Schoen, S. A., Nielsen, D. M., & Baron-Cohen, S. (2014). Sensory over-responsivity in adults with autism spectrum conditions. *Autism*, *18*(4), 428–432.

Ten Brink, A. F., & Bultitude, J. H. (2022). Visual sensitivity in complex regional pain syndrome and fibromyalgia: an online study. *Perception*, *51*(3), 187–209.

Tosta, S., Ferreira, M., Lewine, J., & Anderson, A. (2024). Individualized spectral filters alleviate persistent photophobia, headaches and migraines in active duty military and Veterans following brain trauma. *Brain Injury*, *38*(3), 177–185.

Tyler, C., Apkarian, P., & Nakayama, K. (1978). Multiple spatial-frequency tuning of electrical responses from human visual cortex. *Experimental Brain Research*, *33*(3), 535–550.

Valdez, P., & Mehrabian, A. (1994). Effects of color on emotions. *Journal of Experimental Psychology: General*, *123*(4), 394.

Valentine, C., Wilkins, A. J., Mitcheltree, H., Penacchio, O., Beckles, B., & Hosking, I. (2025). Visual discomfort in the built environment: Leveraging generative AI and computational analysis to evaluate predicted visual stress in architectural Façades. *Buildings*, *15*(13), 2208.

Vandewalle, G., Maquet, P., & Dijk, D.-J. (2009). Light as a modulator of cognitive brain function. *Trends in Cognitive Sciences*, *13*(10), 429–438. http://dx.doi.org/10.1016/j.tics.2009.07.004, URL: https://www.sciencedirect.com/science/article/pii/S1364661309001685.

Vecchia, D., & Pietrobon, D. (2012). Migraine: A disorder of brain excitatory–inhibitory balance? *Trends in Neurosciences*, *35*(8), 507–520. http://dx.doi.org/10.1016/j.tins.2012.04.007.

Ward, J. (2019). Individual differences in sensory sensitivity: A synthesizing framework and evidence from normal variation and developmental conditions. *Cognitive Neuroscience*, *10*(3), 139–157. http://dx.doi.org/10.1080/17588928.2018.1557131.

Ward, J., Agbude, R., Smees, R., Simner, J., & Ronen, I. (2025). The neurochemistry of decreased sound tolerance: A magnetic resonance spectroscopy (MRS) study of misophonia and hyperacusis. *Hearing Research*, Article 109440.

Wilkins, A. J. (1995). *Visual Stress*. Oxford: Oxford University Press.

Wilkins, A. (2012). Origins of visual stress. (pp. 63–78). http://dx.doi.org/10.1093/acprof:oso/9780199589814.003.0004.

Wilkins, A., Allen, P. M., Monger, L. J., & Gilchrist, J. M. (2016). Visual stress and dyslexia for the practicing optometrist. *Optometry in Practice*, *17*(2).

Wilkins, A., & Evans, B. (2001). *Pattern glare test instructions*. London: IOO Sales Ltd.

Wilkins, A. J., & Hibbard, P. B. (2014). Discomfort and hypermetabolism. Presented at AISB 2014 - 50th Annual Convention of the AISB.

Wilkins, A., Huang, J., & Cao, Y. (2004). Visual stress theory and its applicaton to reading and reading tests. *Journal of Research in Reading*, *27*, 152–162. http://dx.doi.org/10.1111/j.1467-9817.2004.00223.x.

Wilkins, A., & Neary, C. (1991). Some visual, optometric and perceptual effects of coloured glasses. *Ophthalmic & Physiological Optics*, *11*(2), 163–171. http://dx.doi.org/10.1111/j.1475-1313.1991.tb00216.x.

Wilkins, A., Nimmo-Smith, I., Tait, A., McManus, C., Della Sala, S., Tilley, A., Arnold, K., Barrie, M., & Scott, S. (1984). A neurological basis for visual discomfort. *Brain*, *107*(4), 989–1017. http://dx.doi.org/10.1093/brain/107.4.989.

Wilkins, A. J., Penacchio, O., & Leonards, U. (2018). The built environment and its patterns: A view from the vision sciences. *Journal of Sustainable Design and Applied Research in Innovative Engineering of the Built Environment*.

Wilson, G. D. (1966). Arousal properties of red versus green. *Perceptual and Motor Skills*, *23*(3), 947–949.

Winterbottom, M., & Wilkins, A. (2009). Lighting and discomfort in the classroom. *Journal of Environmental Psychology*, *29*(1), 63–75.

Yoshimoto, S., Garcia, J., Jiang, F., Wilkins, A. J., Takeuchi, T., & Webster, M. A. (2017). Visual discomfort and flicker. *Vision Research*, *138*, 18–28.

Yoshimoto, S., Iizuka, H., & Takeuchi, T. (2025). Visual discomfort and chromatic flickers. *Vision Research*, *226*, Article 108520.

Zhang, Y., Valsecchi, M., Gegenfurtner, K. R., & Chen, J. (2023). The time course of chromatic adaptation in human early visual cortex revealed by SSVEPs. *Journal of Vision*, *23*(5), 17–17.