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Facial expression categorization predominantly relies on mid-spatial frequencies

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ABSTRACT

Facial expressions are crucial in human communication. Recent decades have seen growing interest in understanding the role of spatial frequencies (SFs) in emotion perception in others. While some studies have suggested a preferential treatment of low versus high SFs, the optimal SFs for recognizing basic facial expressions remain elusive. This study, conducted on Western participants, addresses this gap using two complementary methods: a data-driven method (Exp. 1) without arbitrary SF cut-offs, and a more naturalistic method (Exp. 2) simulating variations in viewing distance. Results generally showed a preponderant role of low over high SFs, but particularly stress that facial expression categorization mostly relies on mid-range SF content (i.e. ~6–13 cycles per face), often overlooked in previous studies. Optimal performance was observed at short to medium viewing distances (1.2–2.4 m), declining sharply with increased distance, precisely when mid-range SFs were no longer available. Additionally, our data suggest variations in SF tuning profiles across basic facial expressions and nuanced contributions from low and mid SFs in facial expression processing. Most importantly, it suggests that any method that removes mid-SF content has the downfall of offering an incomplete account of SFs diagnosticity for facial expression recognition.

1. Introduction

It is widely recognized that facial expressions of emotions play a crucial role in social communication by transmitting signals about internal emotional states and intentions. They can also indicate potential environmental threats, triggering an adaptive response (e.g., to escape) in both the expresser and observer (e.g., Schmidt & Cohn, 2001).

There has been a growing interest in the role played by low-level properties, such as spatial frequency (SF) and orientation (SO), in visual categorization. This highlights how early visual cortices decompose visual stimuli into their constituent elements, similar to Fourier analysis (De Valois et al., 1979; Maffei & Fiorentini, 1973), with different spatial frequencies conveying varying levels of contrast details.

The relationship between SFs and emotion perception has often been explained by the dual-route model, which proposes a distinction between a fast subcortical pathway and a slower cortical pathway. According to this model, the subcortical pathway facilitates the rapid processing and appraisal of threat-relevant stimuli through LSF visual input (e.g., Tamietto & De Gelder, 2010; Vuilleumier et al., 2003), while the cortical pathway processes SF content along a coarse-to-fine gradient, allowing for a more detailed analysis at a slower speed (e.g., Bar, 2003; LeDoux, 2000; Öhman, 2005). Converging evidence from neuroimaging and computational studies supports a LSF advantage in emotion processing, especially for threat-related stimuli like fearful faces (e.g., Mermillod et al., 2009, 2010; Vuilleumier et al., 2003). Due to properties of the human visual system and face stimuli, LSFs are overrepresented in peripheral or distal viewing conditions (e.g., Sowden & Schyns, 2006), which support the LSF advantage over HSF content from this perspective. However, a growing body of evidence has challenged this dual-route model, suggesting that some cortical regions may process information as rapidly as the subcortical route (e.g., Pessoa & Adolphs, 2010), that the supposedly fast subcortical pathway lacks selectivity for spatial frequency or the emotional content of faces (e.g., McFadyen et al., 2017), and that the distinction between low and high

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spatial frequencies remains ambiguous, even within the parallel parvocellular and magnocellular pathways from the retina to the visual cortex (e.g., Skottun & Skoyles, 2008). Instead, alternative models, such as the "multiple-waves model", propose that emotional stimuli are processed through the dynamic coordination of multiple cortical networks, rather than a strict division between subcortical and cortical pathways (Pessoa & Adolphs, 2010).

Moreover, peak contrast sensitivity of the human visual system occurs at mid-range spatial frequencies (MSF) of approximately 2–5 cycles per degree (cpd), rather than at lower frequencies. (e.g., Campbell & Robson, 1968). This corresponds to about 12 cycles per face (cpf) when viewed from a distance of about 1.5 m (6 deg) to 2 m (4 deg) (Oruc & Barton, 2010). Importantly, this MSF content is known to play a critical role for face identification (~8–20 cpf; e.g., Collin et al., 2014; Gaspar et al., 2008), potentially reflecting the visual system's adaptation to facial stimuli (Keil et al., 2008). Thus, we might also expect recognition of facial expressions to rely on similar mid-range SF content.

The precise role of LSFs in emotion perception remains debated. While some contrasted the role of LSFs for happiness and HSFs for sadness recognition, using low-pass and high-pass filters (Kumar & Srinivasan, 2011), others have shown the importance of mid-to-high SF information in the detection and recognition of expressions by using SF noise masking (Gao & Maurer, 2011), or band-pass filtering (Goren & Wilson, 2006) both accounting for mid-range SFs. Bubbles methodology was also used to simultaneously explore the reliance on spatial (i.e. regions of the face) and SF information. Results suggest some processing patterns varying across facial expressions with fear relying on the wide-opened eye region (mid-to-high SFs), happiness and surprise on the mouth region (mid-to-low SFs), anger on the frown of the eyebrows (mid-to-low SFs), disgust on the nasolabial folds (mid-to-low SFs), and sadness on the crease of the forehead and corner of the mouth (mid-to-high SFs; e.g., Smith et al., 2005; Smith & Merlusca, 2014). Others have indirectly investigated the role of SFs by manipulating the distance (Smith & Schyns, 2009) or the location in the visual field where facial expressions are perceived (Smith & Rossit, 2018). These studies recreate naturalistic situations where signal degradation occurs on a fine-to-coarse gradient (i.e., increasing distance/periphery first alters HSF content, then MSF, and so on). Similarly to other results, happiness and surprise were the best-recognized facial expressions in peripheral vision or at a further distance. Interestingly, performance significantly dropped at distance where mid-range spatial frequencies (MSF) were no longer accessible, highlighting their crucial role in expression recognition.

Although studies mentioned above have undoubtedly contributed to advancing our understanding of the relationship between SFs and facial expression recognition, none has yet provided a definitive understanding of which SFs are most diagnostic for this process. Previous reviews on the role of SF in identity and facial expression recognition (De Cesarei & Codispoti, 2013; Jeantet et al., 2018) highlighted methodological variability in SF manipulation methods and task demands, potentially leading to conflicting results. Most of these studies have used arbitrary cut-offs to define low and high SFs (e.g., LSF defined below 8 cpf in Kumar & Srinivasan, 2011; between 2 and 8 cpf in Goffaux & Rossion, 2006; below 6 cycles per image in Vuilleumier et al., 2003; and HSF defined above 32 cpf in Kumar & Srinivasan, 2011 or above 24 cycles per image Vuilleumier et al., 2003) which overlooks the potentially crucial contribution of MSFs in facial expression processing.

Our primary objective was to parametrically investigate SF processing and establish precise tuning profiles for the recognition of all six basic facial expressions of emotions, along with neutrality and pain. Note that this study primarily focuses on the recognition component of facial expressions, specifically examining expressions presented at their apex. According to vision perception models, recognition is understood as the process of identifying an object based on its visual representation stored in memory. For example, the RAP framework (Gosselin & Schyns, 2002) proposes that the visual information which can be efficiently used by observers to categorize objects, referred to as potent information, results from an interaction between the visual information available in the stimuli and the visual representation stored in the observer's memory from prior encounters with similar objects. In this context, our present work aimed to identify the SF information that is most relevant—i.e., potent information—for categorizing basic facial expressions. As findings pertaining to pain are reported elsewhere (Charbonneau et al., 2021) they will not be further addressed unless otherwise pertinent. To establish SF tuning profiles, we used in Experiment 1 a variant of bubbles that treats SFs as a continuous variable, randomly sampling SFs on a trial basis, thereby allowing a much more precise assessment of their respective contributions (Willenbockel et al., 2010). Importantly, SF bubbles make no a priori decisions regarding SF cutoffs.

In Experiment 2 we manipulated the perceived distance at which expressions were recognized to generalize SF tuning profiles (Exp. 1) to a more naturalistic context. For instance, in everyday situations, one might perceive a face from a distance, such as at the end of a hallway, or up close, when standing face-to-face with someone as an elevator door opens. We predict that when manipulating the distance at which an expressive face is viewed, the most consequential drops in recognition accuracy should occur at distances that prevent processing of the most diagnostic SF information for this facial expression. For example, when distances are greatest (i.e., only LSF content can be processed), expressions with a relatively higher contribution of LSFs, should be better recognized relative to other expressions. This study will test these predictions using two complementary methods, thus providing a better understanding of the impact of SFs on facial expression recognition.

2. General methods

2.1. Participants

Twenty White healthy adult Canadian participants aged between 18 and 40 years old took part in each experiment for a total of 40 participants (Experiment 1: 10F, M = 26 yo, SD = 3.4; Experiment 2: 14F, M = 21.45 yo, SD = 3.52). Data was collected between 2016 and 2019. The sample size for each experiment was informed by similar studies on emotion recognition and SFs and was determined a priori to achieve a statistical power of 0.80, assuming an effect size comparable to those reported by Smith and Schyns (2009) and Kumar and Srinivasan (2011), with Cohen's d values of 0.92 and 2.5, respectively (G*Power; Faul et al., 2007). Participants provided their written consent to take part in the experiments and all had normal or corrected-to-normal vision. Procedures received approval from the research ethics committee at Université du Québec en Outaouais.

2.2. Material and stimuli

Stimuli came from the validated STOIC database (Roy et al., 2007; Simon et al., 2008), and consisted of 80 images depicting the faces of 10 different White individuals. Each individual was pictured displaying a neutral or emotional (i.e. anger, disgust, fear, happiness, sadness, surprise, and pain) facial expression. All images were gray-scaled before mean luminance, contrast, and SF spectra were equated across images using the SHINE toolbox (Willenbockel et al., 2010). A gray mask with an elliptic aperture was applied to each face to hide external features. Stimuli were displayed on a 1080p calibrated LCD monitor with a 100 Hz refresh rate. Experimental programs were written in Matlab (Natick, MA), using custom code and functions from the Psychophysics Toolbox (Pelli, 1997; Brainard, 1997; Kleiner et al., 2007). The viewing distance was maintained at 46.5 cm using a chinrest.

2.3. Procedure

Prior to the experiments, participants were instructed to look at the emotional and neutral faces displayed on a computer screen until they felt confident that they could accurately recognize all facial expressions. At this point, a practice session began. Each practice trial began with a centered fixation cross displayed 500 ms. Then, one of the 80 face stimuli was randomly selected and presented for 300 ms. Face width was 5.72 degrees of visual angle. Participants were tasked with choosing the appropriate emotion label using the assigned keyboard key. No time limit was imposed, and no direct accuracy feedback was provided. After a response was entered, the next trial began. The practice phase ensured participants could accurately label facial expressions. The practice was repeated as many times as necessary and completed when performance reached at least 90 % correct over two consecutives 160 trials blocks. After practice, participants then began their assigned experimental task (i.e., Experiment 1 or 2). Experiments were conducted across multiple sessions, with each session beginning with a practice phase. Participants were encouraged to take breaks as needed during the sessions.

3. Experiment 1: SF tuning profiles

Participants completed 26 blocks of 160 trials each for a total of 4,160 trials per participant. This is consistent with other studies using SF bubbles (Tadros et al., 2013; Willenbockel et al., 2010) since they typically favor large numbers of trials (e.g., ~2000–4000 trials/subject). Each trial began with a centered fixation cross displayed 500 ms. Then, one of the 80 face stimuli was randomly selected, “SF-bubblized”, and presented for 300 ms. Face width was the same as in the practice session. Participants were tasked with choosing the appropriate emotion label using the assigned keyboard key. Again, there was no time limit or accuracy feedback. Immediately after a response was entered, the next trial began. To reveal visual information useful for the recognition of basic facial expressions, faces were sampled in Fourier space using spatial frequency (SF) bubbles (Willenbockel et al., 2010). SF bubbles randomly sample image SF content on a trial basis, and its effect on accuracy is revealed with classification image techniques, which are analogous to regression analysis (Gosselin & Schyns, 2001). Across many trials, this method allows to independently assess the contribution of every SF to visual categorization (see Fig. 4 in Willenbockel et al., 2010).

Fig. 1 illustrates the creation process of “SF-bubblized” stimuli. First, the base stimulus was padded with a uniform gray background (Fig. 1a) to minimize edge artifacts. Second, the padded stimulus was converted to Fourier space using Fast Fourier Transform (FFT; Fig. 1b). A random SF filter was then created starting with a monotonous vector of size $2wk$ elements, where w is the original stimulus width (i.e., 256 pixels) and k (i.e., 20) is a constant that determines sampling smoothness. On each trial, 10 SF samples (i.e., ones) were randomly dispersed across the 10,240 elements, creating a binary SF sampling vector (Fig. 1c). The binary sampling vector was then convolved with a Gaussian kernel, or bubble (Fig. 1d) with FWHM equal to 1.8 cycles per image, resulting in a smooth sampling vector (Fig. 1e). This smooth sampling vector was then log-scaled (Fig. 1f) to adjust for human contrast sensitivity (De Valois & De Valois, 1980). The resulting w-elements filter was then rotated on its DC origin to create an isotropic two-dimensional smooth sampling matrix (i.e., SF bubbles) of size w x w (Fig. 1g). Finally, the padded stimulus Fourier spectrum was sampled with SF bubbles by dot-multiplication (Fig. 1h), and the product was converted back to the image domain by applying inverse FFT (Fig. 1i). Finally, the padded region was cropped, preserving only the initial w x w central region. To adjust task difficulty and maintain 56.25 % correct responses (i.e., halfway between floor and ceiling), a proportion of Gaussian white noise was added to the SF-filtered stimulus. This proportion was manipulated on a trial basis using QUEST (Watson & Pelli, 1983).

3.1. Analysis and results

Data were analyzed using Matlab version: 8.6 (R2015b) and IBM SPSS Statistics (Version 29.0.0.0.). SFs for accurate facial expression

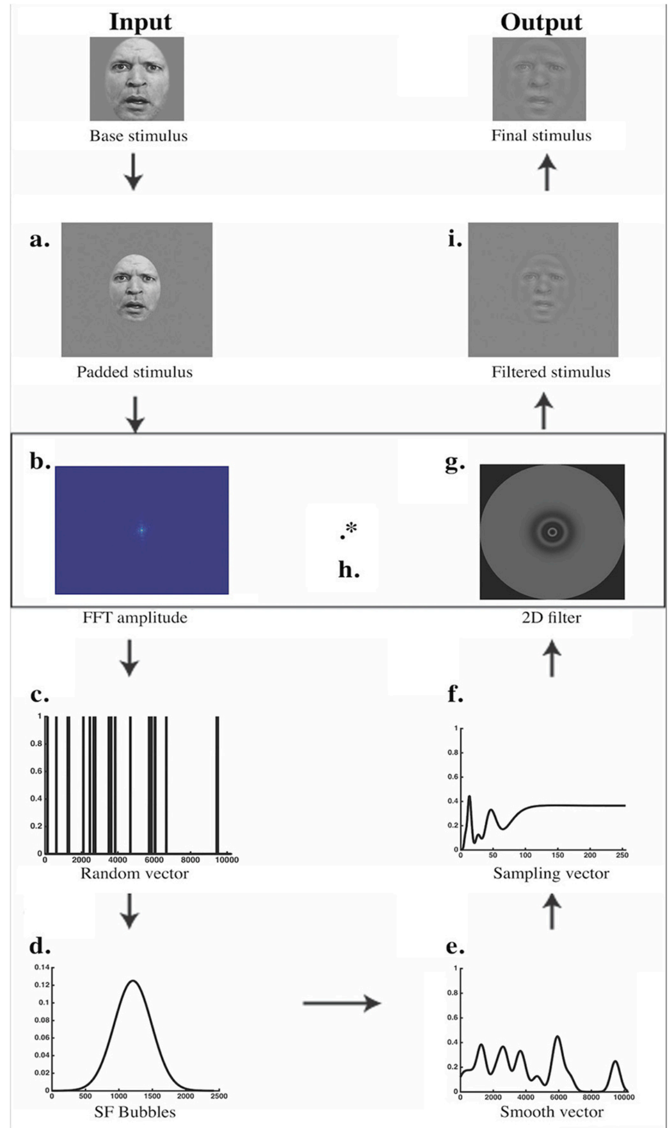

Fig. 1. Creation of a “SF-bubblized” stimulus.

categorization were analyzed by computing classification images which represent the strength and direction of association between SF and performance. Classification image analysis amounts to a multiple regression analysis of SF sampling vectors on accuracies across trials. Specifically, classification vectors (i.e., weighted sums of SF sampling vectors) were calculated individually and for each emotional expression by allocating positive weights to filters that led to correct responses and negative weights to incorrect responses. Weights were calculated by standardizing (converting into z-scores) raw accuracy scores (ones and zeros) on a subject basis; thus, equal weight was given to correct and incorrect responses. In so doing, it is assumed that filters presented on correct trials contained at least some useful SF content, and inversely, filters presented on incorrect trials contained useless or even detrimental SF content. Classification vectors were then smoothed using a Gaussian kernel with a standard deviation equal to 2.5 cycles per image. Resulting individual classification vectors were standardized using the mean and standard deviation of the null hypothesis, which were calculated using the Stat4Ci toolbox (Chauvin et al., 2005). To assess statistical significance, t-scores were first computed, for each SF and each expression. To carry this, we divided averaged individual z-scores by their corresponding standard error. This allows for the consideration of between-subjects variance, effectively applying a correction that is proportional to this variance. Statistical significance of the resulting classification vectors (in *t*-scores) was assessed by applying a pixel test from the Stat4Ci toolbox, $t_{Crit} = 3.98$, $p < 0.05$ (see the dashed line in Fig. 2). The pixel test corrects for multiple comparisons across SFs but also takes into account the spatial correlation inherent to smoothed classification images. SF tuning peaks for individual expressions were estimated on *t*-score vectors using a "*50 % area frequency measure*" (*50 % AFM*), which is less sensitive to the shape of tuning curves (see, for similar applications across spatial frequency bubbles and spatial orientation bubbles, Duncan et al., 2017). In essence, this 50 % AFM corresponds to the SF that splits the total area under the curve (AUC) of statistically significant SFs (i.e., $t > t_{crit}$) in two 50 % sub-AUCs. It can therefore be seen as the median statistically significant SF.

Fig. 2 shows SF tuning for each facial expression. Precisely, *50 % AFM* measures reflected a predominant contribution of MSF facial content across most expressions: anger (13.01 cpf), disgust (12.2 cpf), fear (13.35 cpf), neutrality (12.31 cpf), and sadness (10.37 cpf). Only happy (5.92 cpf) and surprised (6.42 cpf) expressions reflected a predominant contribution of LSF facial content. To better compare our results with previous studies that used arbitrary cut-offs, we quantified usefulness of LSFs, MSFs, and HSFs by applying similar cut-offs to the data. Specifically, we conducted, for each expression, a bootstrap analysis of classification vectors (*t*-scores) that consisted of 10,000 Monte Carlo simulations, i.e., resamples of size n = 20 with replacement. For each simulation and expression, we calculated the trapezoidal numerical integration of significant *t*-scores cumulated between 2 and 8 cpf (LSF), between 8 and 32 cpf (MSF), and at or above 32 cpf (HSF). Note that classification vectors were log-scaled, such that LSFs and MSFs, which spanned exactly 2 octaves, were equally represented in this analysis. Finally, we divided each outcome by the sum of all significant *t*-scores to obtain a proportion of total diagnostic information. The use of these SF ranges ensures that the comparison is constant over the entire SF range, so that each range represents two octaves of SF information. Table 1 presents these proportions (expressed in percentages). First, we note that the contribution of LSFs was statistically greater than the contribution of HSFs for all expressions (all *ps* < 0.034), except for fear (p = 0.119). Second, for every expression except happiness and surprise, the contribution of MSFs was statistically greater than the contribution of LSFs, all ps < 0.042 (the effect was marginally significant for sadness, p = 0.079). Note that for happiness and surprise, the contribution of LSFs and MSFs was statistically similar, ps > 0.856. Finally, the contribution of MSFs was statistically greater than the contribution of HSFs for all expressions (all *ps* < 0.002).

Table 1
Proportion (in %) of useful information across different spatial frequency cut-offs.

Facial expression	LSF	MSF	HSF	*p* value LSF > HSF	*p* value MSF > LSF	*p* value MSF > HSF
Anger	19.00 (6.18)	77.78 (5.99)	3.22 (2.37)	0.014	<0.001	<0.001
Disgust	16.59 (4.48)	82.69 (4.64)	1.2 (2.72)	0.013	<0.001	<0.001
Fear	29.71 (9.39)	61.19 (9.35)	8.70 (8.07)	0.119	0.042	0.002
Happiness	68.84 (8.10)	30.70 (8.32)	0 (0.02)	<0.001	0.984	<0.001
Neutral	8.59 (3.24)	91.41 (3.63)	0 (2.18)	0.034	<0.001	<0.001
Sadness	30.63 (10.76)	69.37 (10.15)	0 (2.33)	<0.004	0.079	<0.001
Surprise	66.28 (14.07)	33.72 (14.45)	0 (0.04)	<0.001	0.856	<0.001

Note. The proportion values presented in this table are expressed as percentages (with one standard deviation in parentheses) for each facial expression. Cut-off represents information between 2 and 8 cpf (LSFs), between 8 and 32 cpf (MSFs), and above 32 cpf (HSFs).

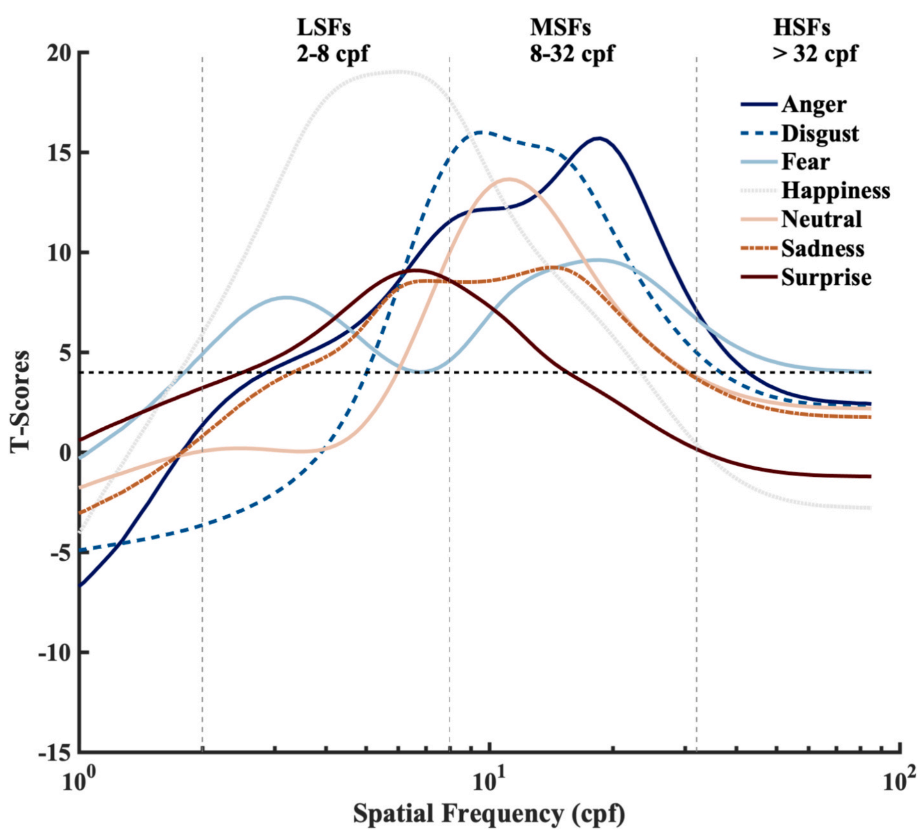

Fig. 2. SF tuning for basic facial expression categorization as revealed by the SF bubble's method.

4. Experiment 2: Perceived distance

In Experiment 2, participants completed 15 blocks of 160 trials for a total of 2,400 trials per participant. Each trial began with a centered fixation cross displayed 500 ms. Then, one of the 80 face stimuli was randomly selected and presented for 300 ms. A random noise mask was subsequently presented for 150 ms. Participants were tasked with choosing the appropriate emotion label (out of eight) using the assigned keyboard key. No time limit was imposed. Feedback was not provided. Immediately after a response was registered, the next trial began. Note that the face stimuli and image sizes were presented randomly, rather than continuously simulating a face approaching or moving away. Stimuli were created using the Laplacian Pyramid toolbox (Burt & Adelson, 1983), a method that recursively applies low-pass filters to images, each time removing their highest SF octave, and down-sampling the outcome by a factor of two. This resulted, for each face and expression combination, in a series of six images that progressively decreased in size (face widths corresponded to 3.26, 1.63, 0.82, 0.41, 0.2, 0.1 degrees of visual angle), thereby simulating a doubling of viewing distance with each size reduction (i.e., 1.2, 2.4, 4.8, 9.6, 19.2, and 38.4 m, respectively; see Fig. 3). Available SF content thus corresponded to applying low-pass filters of 128, 64, 32, 16, 8, and 4 cycles per face, respectively. The original image size was 384 x 384 pixels (~6.9 cm), which corresponds to 3.26 degrees of visual angle at a viewing distance of 122 cm from the screen.

4.1. Analysis and results

Data were analyzed using Matlab version: 8.6 (R2015b), Natick Massachusetts: The MathWorks Inc., and IBM SPSS Statistics (Version 29.0.0.0.). Performance on the categorization task was calculated using unbiased hit rates (Fig. 4). This modified measure of sensitivity, from signal detection theory, is advised for facial expression recognition tasks since it is independent from response biases (Armistead, 2013), which are pervasive with facial expressions of emotions (e.g., systematically confusing surprise with fear; Elfenbein et al., 2002). Statistical analyses were carried out on relative UHRs (though absolute UHRs are also reported in the supplementary materials), which consisted of expressing performance at each simulated distance as a proportion of maximum performance, achieved at the shortest distance (1.2 m). This provided a clearer picture of the extent of performance degradation as a function of increases in perceived distance, and facilitated direct comparison of this effect across emotions.

A 6 (Distance) x 7 (Emotion) repeated measures ANOVA was performed. A Greenhouse-Geisser correction was applied whenever the sphericity assumption was violated. Note that we did not consider the main effect of *Emotion* on relative UHR as it is confounded with distance. The effect of *Distance* was significant, $F(1.81, 34.41) = 868.28$, $p < 0.001$ ($\eta 2p = 0.98$), which globally showed better proximal vs. distal performances. However, this effect was not uniform across distances. Most notably, increasing distance from 9.6 to 19.2 m (equivalent to removing MSF content between 8 cpf and 16 cpf) had the largest negative impact on expression recognition performance (see Table S1 in Supplemental materials for full results). The *Distance* by *Emotion* interaction was also significant, $F(8.62, 163.78) = 11.73$, $p < 0.001$ ($\eta 2p = 0.38$).

The interaction was decomposed by computing separate one-way repeated measures ANOVAs (i.e., one per facial expression), each time testing the effect of *Distance*. Every expression showed a significant effect of distance, with better proximal vs. distal performance (anger: $F(1.91, 36.22) = 684.62$, $p < 0.001$ ($\eta 2p = 0.97$); disgust: $F(2.28, 43.39) = 396.60$, $p < 0.001$ ($\eta 2p = 0.95$); fear: $F(2.67, 50,82) = 326.03$, $p < 0.001$ ($\eta 2p = 0.95$); happiness: $F(2.28, 43.22) = 570.62$, $p < 0.001$ ($\eta 2p = 0.97$); neutral: $F(3.04, 57.69) = 446.04$, $p < 0.001$ ($\eta 2p = 0.96$); sadness: $F(2.93, 55.62 = 364.83$, $p < 0.001$ ($\eta 2p = 0.95$); surprise: $F(2.66, 50.53) = 254.77$, $p < 0.001$ ($\eta 2p = 0.93$).

Follow-up paired samples *t*-tests were performed for five pairs of adjacent distances (i.e. 1.2 m with 2.4 m, 2.4 m with 4.8 m, and so forth; $p = 0.05/5$). Fig. 5 charts every contrast (see also Tables S2–S6 in Supplemental materials for full follow-up *t*-tests results). First, we note that sadness was the only expression for which relative UHRs statistically differed between the two most proximal distances (1.2 m and 2.4 m). However, several facial expressions saw a considerable performance decline as distance further increased. Despite differences in distance effects across facial expressions, the most substantial drop in performance for all facial expressions occurred between 9.6 m and 19.2 m (see also Fig. 4). Finally, Fig. 6 shows the full confusion matrices underlying absolute UHR as a function of distance.

To better quantify distance thresholds across expressions, we applied curve-fitting using the Palamedes toolbox (Prins & Kingdom, 2018). The distance threshold for a given expression corresponds to the distance at which relative UHR reaches 50 % (i.e., halfway between floor and ceiling performance) for that expression, such that a higher distance threshold implies this expression can be recognized from further away. It is inversely proportional to cpf threshold, such that a high distance threshold amounts to a lower cpf threshold. Results are reported in Table 2 and details on curve-fitting analysis are reported in Supplemental materials. Results were largely consistent with predictions drawn from Experiment 1. For instance, every distance threshold fell within 9.63 m–16.82 m; these correspond to MSFs, with cpf thresholds ranging between 9.13cpf and 15.67cpf. Furthermore, thresholds for happiness and surprise were at a farther distance (14.81–16.82 m) and lower SF (9.13–10.37cpf), compared to expressions of anger, disgust, neutrality, and sadness (9.63–10.61 m; 14.47–15.94cpf). This indicates happy and surprised expressions were better recognized from farther away, using relatively lower SF face content, and is again consistent with results of Experiment 1.

Seeing as every SF threshold measured in Exp. 2 fell within the range of MSFs, we wondered whether proximity to the MSF mid-point (i.e., 16 cpf) would concord with usefulness of MSFs in Exp. 1, such that for instance sadness (threshold at 15.94 cpf) would manifest greater MSF usefulness than surprise (threshold at 9.13cpf). Seeing as every threshold fell below 16 cpf, we simply performed an exploratory correlation analysis between group-averaged SF thresholds (Exp. 2) and percent contributions of MSFs (Exp. 1) across expressions. Results showed this was indeed the case, $r = 0.963$, $p = 0.0023$: Expressions for which the threshold was higher and thus closer to the MSF mid-point in Exp. 2 were more likely to show greater reliance on MSF information in Exp. 1. Furthermore, a bootstrap analysis that consisted of 10,000 Monte Carlo resamples showed this result was reliable, 95 % CI = [0.343, 0.999]. As for slopes, there was a general steepness indicative of an inflection point (i.e., non-linearity). In other words, sensitivity to information increased as it got closer to the threshold and decreased as it got farther from it. However, some slopes (e.g., anger, disgust, and happiness) did appear steeper than others (e.g., sadness, neutrality and

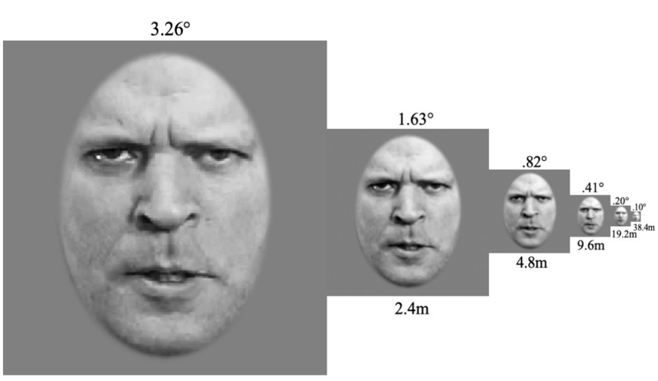

Fig. 3. Examples of stimuli created with the distance manipulation method.

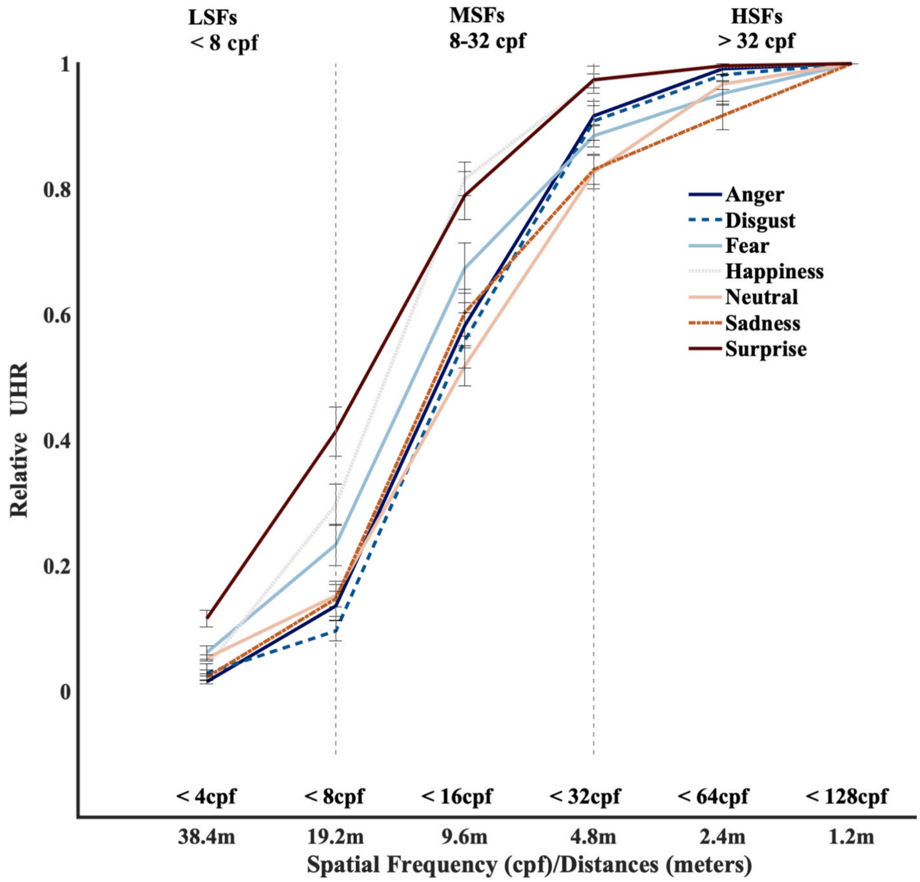

Fig. 4. Relative unbiased hit rates for emotion categorization as a function of viewing distance.

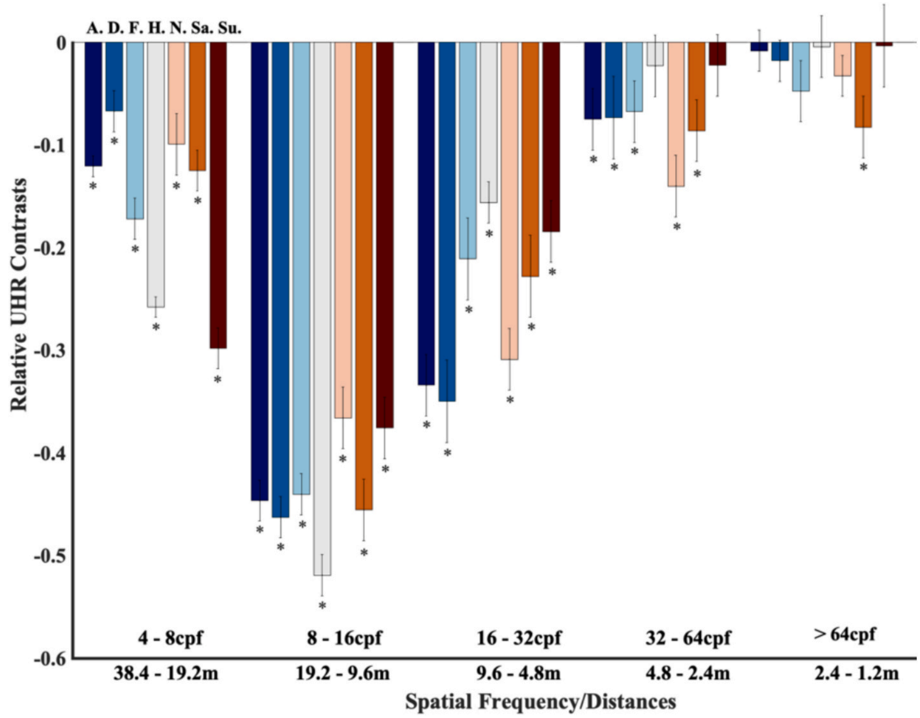

Fig. 5. Relative Unbiased Hit Rates Contrasts.

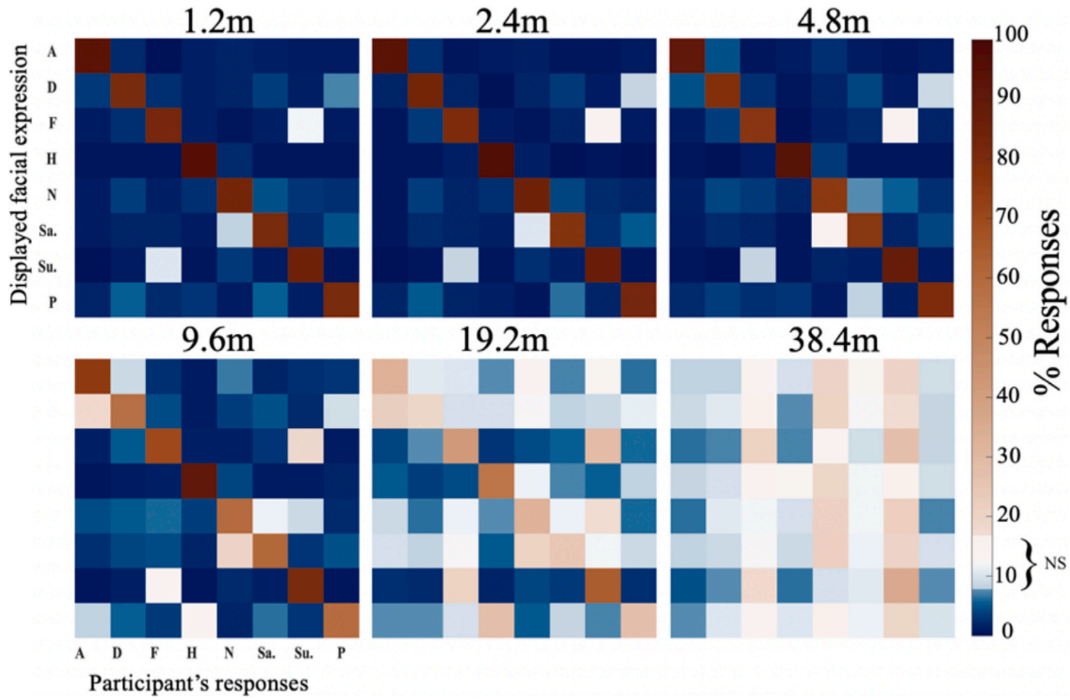

Fig. 6. Full confusion matrices underlying performance at each distance.

Table 2
Curve fitting parameters characterizing the relationship between facial expression categorization and distances.

Facial expression	α (meters/cpf)	β	Deviation (*p*Dev)	*R*2
Anger	2.86 (10.61/14.47)	1.21	0.01(0.65)	1
Disgust	2.92 (10.14/15.15)	1.15	0.05(0.12)	0.99
Fear	2.69 (11.88/12.93)	0.88	0.06(0.25)	0.99
Happiness	2.38 (14.81/10.37)	1.29	0.02(0.10)	0.99
Neutral	2.97 (9.81/15.67)	0.92	0.02(0.22)	0.99
Sadness	2.99 (9.63/15.94)	0.89	0.11(0.24)	0.98
Surprise	2.19 (16.82/9.13)	1.03	0.01(0.99)	1

Note. Threshold (α) corresponds to the distance at which relative UHR for a given expression reaches 50% (i.e., halfway between floor and ceiling). Equivalents for that parameter, in both meters and cpf, are also displayed. Slope (β) represents the function's steepness, indicating sensitivity and selective use of information near this threshold. Goodness of fit was evaluated with the estimation of the deviance (1,000 bootstrap iterations). pDev represents the proportion of simulation deviance that was greater than in the actual data; higher equals better fit). The coefficient of determination (*R*2) for each facial expression is reported in the last row.

fear). Seeing as peak SF tuning (*t*-score) is also a measure of sensitivity to information–in that it represents the inflection point in the cumulative SF tuning profile–we wondered whether expressions with steeper slope parameters (Exp. 2) would concord with higher peak *t*-scores (Exp. 1). A second exploratory correlation analysis between slopes and peak *t*-scores showed this was indeed the case, $r = 0.85$, $p = 0.015$ (CI 95 % = [0.328, 0.992], estimated with 10,000 Monte Carlo simulations.

5. Discussion

Experiment 1 reveals that the key SF content for facial expression recognition predominantly falls within a narrow band, spanning from 5.92 cpf to 13.35 cpf. In Experiment 2, performance is affected at both short and long distances, but as expected from results of Exp. 1, the most significant impact occurs when perceived distance leads to the loss of MSF content (between 8 and 32 cpf). Several parallels are identified between both experiments. Notably, facial expressions that rely more on LSFs (i.e. happy and surprise in Exp. 1) are generally more resilient to increases in perceived viewing distance. Moreover, greater reliance on MSF content (Exp. 1) is associated with distance thresholds that are more centered on MSFs (i.e., closer to 16 cpf).

5.1. Importance of mid-range spatial frequencies

Our results show that expression recognition heavily rests on the processing of MSFs. They contribute more than LSFs to most expression recognition (i.e. except happiness and surprise) and more than HSFs across all expression categories. They are also consistent with the human contrast sensitivity function (CSF) typically peaking at about 2–5 cpd (Campbell & Robson, 1968). Although faces can be viewed at varying distances, our face diet is predominantly shaped by interpersonal interactions, which usually occur at distances of about 2 m (Oruc & Barton, 2010; Oruc et al., 2019). At this distance, facial mid-spatial frequency (MSF) content roughly matches the peak sensitivity of the human CSF. Consequently, these facial MSFs are the most relied-upon content at interpersonal distances (Owsley & Sloane, 1987), and performance plummets when this information becomes inaccessible (e.g., Schyns & Oliva, 1999).

5.2. Methodological considerations

Our results replicate many findings, highlighting the role of LSFs when compared to HSFs in the recognition of facial expressions. The contribution of LSFs is significantly larger than that of HSFs for almost all facial expressions, except for fear, where the difference is marginal. Fear recognition differs from other expressions due to a dependence on higher SFs, consistent with previous work suggesting a reliance on the eye region (Smith et al., 2005) and mid-to-high SFs (e.g., Morawetz et al., 2011). This pattern also explains the lack of advantage of LSFs over MSFs, as fear recognition primarily relies on MSFs (over 60 % of diagnostic information). These results might appear inconsistent with the commonly reported importance of LSFs in processing specific facial expressions (e.g., fear; (Mendez-Bértolo et al., 2016); Pourtois et al., 2005). However, these findings can be reconciled by considering methodological details that influence our understanding of visual strategies used in facial expression categorization.

In light of the findings of De Cesarei and Codispoti (2013), who emphasize methodological differences in studies investigating FS in emotion perception, we suggest that at least two methodological details are important to consider. First, many studies use arbitrary cut-offs that often exclude MSFs, comparing solely the contribution of LSFs (often < 8 cpf) and HSFs (often > 32 cpf). Our experimental framework, on the other hand, allows the exploration of the complete spatial frequency spectrum instead of merely focusing on its extremes. Our results are, therefore, consistent with other investigations that considered SFs in a more continuous way (e.g., Gao & Maurer, 2011). Secondly, the task parameters, such as the number and types of expression alternatives (e.g., 2 vs. 7 choices; neutrality and fear vs. anger and fear), can significantly influence the utilization of SF information in facial expression perception (Schyns & Oliva, 1999). While there is no optimal decision regarding the number of expressions to include, our selection was made with the aim of aligning with certain real-life scenarios. For instance, while we might have expectations about facial expressions in specific contexts (e.g., at a funeral home), it is uncommon in our day-to-day experiences to know in advance what facial expressions others will display. In experimental settings, such as in a fear detection task (fear vs neutral), the absence of neutrality necessarily implies the presence of fear, and vice versa. However, real-life observers cannot rely on such shortcuts. These methodological factors can also have a compounding effect inflating the contribution of LSFs. Thus, overlooking these important factors can limit or even warp our understanding of perceptual mechanisms involved in facial expression processing.

5.3. Reappraising the role of low spatial frequencies

The disproportionate reliance on MSFs invites reconsideration of the prominent role often attributed to LSF, especially given the poor performance observed when only LSF content was accessible to observers. However, this does not imply that LSF content plays no role in facial expression perception; on the contrary, intriguing patterns emerge when only LSF information is available. First, confusion matrices show that surprise is perceived almost twice as often when presented at a very great distance despite the UHRs compensating for response biases (Fig. 6; see Smith & Rossit, 2018 for analogous results in visual periphery). Second, neutrality was the second most likely response, perceived about one and a half times more often than presented. In other words, when only very low SF content was available, stimuli perceived as emotional were mostly classified as surprise, and stimuli perceived as non-emotional as neutrality. These findings suggest that LSF facilitates the detection rather than the recognition of facial expressions. One hypothesis is that surprise, often ambiguous and turning into expressions like "fearfully surprised" (Du et al., 2014), primarily capture observer attention, particularly in the periphery, prompting rapid refocusing and detailed discrimination. This might explain why emotional content detection was feasible at distances where detailed discrimination was limited, often resulting in the emotion being labeled as surprise. One interesting avenue to explore is whether LSF supports the detection of emotionally expressive faces in the visual periphery and brings them into focus for fine-grained processing, while MSF content supports recognition itself.

5.4. Differences across facial expressions

Comparing SF tuning curves highlighted distinct perceptual strategies across facial expressions, likely due to heterogeneity in their facial movements and features. Extension movements, for instance, tend to produce broadening of facial features, which are typical of expressions tuned toward lower SFs, such as surprise (mouth opening) and happiness (mouth widening). Contraction movements, on the other hand, tend to produce narrowing of facial features, which are often found in expressions tuned toward relatively higher SFs, such as disgust (nose wrinkling), anger (frowning), and sadness (squinting).

The fear expression however is somewhat paradoxical: it is easily detected, compared to expressions such as anger, disgust and sadness (Smith & Rossit, 2018), but often confused with surprise, making recognition challenging (see Fig. 6). It is generally better detected than recognized, which is unusual among emotions (Smith & Rossit, 2018). Fear is associated with a bimodal SF tuning profile, peaking in both LSF (3.67 cpf) and MSF (17.33 cpf) ranges, reflecting its extension and contraction movements of both upper and lower facial features (e.g., mouth and eyes widening, eyebrows being pulled together). Studies suggest that the eye region and its higher SF content are crucial for recognizing fear (Adolphs et al., 2005; Fiset et al., 2017), while LSF content in the mouth aids detection but may increase confusion if not complemented by more in-depth information processing (e.g., Sweeny et al., 2013). Research on facial expression dynamics also indicates that fear and surprise might initially be perceived as similar expressions of "fast-approaching danger," relying on lower SF content (Jack, Garrod, & Schyns, 2014; Smith & Schyns, 2009), which might improve detection in peripheral or brief views but increases confusion if higher SF content is not processed (Smith & Rossit, 2018; Sweeny et al., 2013).

5.5. Limitations, constraints on generality, and future directions

One limitation on generalization is that the study used static and posed expressions, which may lack ecological validity. Evidence suggests that perceptual strategies might differ for dynamic expressions, which often show a shift toward lower SF information (Plouffe-Demers et al., 2019). Posed expressions usually lead to similar strategies as spontaneous ones (Saumure et al., 2018); therefore, these limitations are unlikely to affect the generalizability of our results. However, studying how perceived distance affects spontaneous and dynamic expressions could improve ecological validity. Furthermore, to more accurately reflect a naturalistic context, experimental paradigms could incorporate dynamic facial expressions, in which the distance between the observer and an expressive face is continuously manipulated as the face approaches or recedes. Given that diagnostic spatial frequencies are known to vary depending on whether the image is approaching or receding (Brady & Oliva, 2012), this could suggest that changes in certain facial expressions may be more easily perceptible depending on the direction of movement.

A second potential limit to generalization is our reliance on a uniformly Western sample. Cross-cultural studies have shown differences in visual and emotional perception, including SF processing (e.g. Blais et al., 2008; Jack et al., 2009, 2012), with Easterners generally relying more on lower SF content than Westerners (Estéphan et al., 2018; Tardif et al., 2017). This suggests that Easterners might be less affected by distance changes compared to Westerners, though this is speculative as no study has systematically explored cultural effects on SF tuning in emotion recognition. Despite possible cultural differences in perceptual strategies, we believe these would not significantly alter the relationships we observed between SF tuning profiles and distance manipulations. Therefore, the sample homogeneity is unlikely to greatly impact the generalizability of our results.

6. Conclusion

Our results supported the advantage of LSF over HSF information during emotion perception. Importantly, however, our results show this portrait often pictured in the literature is reductive in that it entirely overlooks how recognition of most expressions relies on mid-range SF content to an even greater extent. Importantly, investigations into facial expression perception should ideally consider the whole SF spectrum and results should carefully be interpreted in regard to task demands. This would avoid the possible pitfalls of distorted understanding of how these processes operate, and lead to more generalizable results.

CRediT authorship contribution statement

Isabelle Charbonneau: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Justin Duncan:** Writing – review & editing, Visualization, Validation, Supervision, Software, Formal analysis. **Caroline Blais:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization. **Joël Guérette:** Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Marie-Pier Plouffe-Demers:** Writing – review & editing, Writing – original draft, Validation, Supervision. **Fraser Smith:** Writing – review & editing, Resources, Methodology, Conceptualization. **Daniel Fiset:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, 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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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.visres.2025.108611.

Data availability

This study was not preregistered. Data, analysis code, and research materials are available at: https://osf.io/cm7qh/?view_only=2a60a49a474f4f26881ef2052db00330.

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