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Alexithymia explains atypical spatiotemporal dynamics of eye gaze in autism

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1 Highlights

- 2 • Atypical eye gaze is thought to underlie impaired emotion recognition in autism.
- 3 • Mixed evidence of atypical eye gaze in autism may be explained by alexithymia.
- 4 • Novel methods reveal alexithymia is the best predictor of temporal dynamics of gaze
- 5 to eyes.
- 6 • Atypical eye gaze in alexithymia reflects reduced modulation by top-down priors to
- 7 emotion.

Abstract

Recognition of emotional facial expressions is considered to be atypical in autism. This difficulty is thought to be due to the way that facial expressions are visually explored. Evidence for atypical visual exploration of emotional faces in autism is, however, equivocal. We propose that, where observed, atypical visual exploration of emotional facial expressions is due to alexithymia, a distinct but frequently co-occurring condition. In this eye-tracking study we tested the alexithymia hypothesis using a number of recent methodological advances to study eye gaze during several emotion processing tasks (emotion recognition, intensity judgements, free gaze), in 25 adults with, and 45 without, autism. A multilevel polynomial modelling strategy was used to describe the spatiotemporal dynamics of eye gaze to emotional facial expressions. Converging evidence from traditional and novel analysis methods revealed that atypical gaze to the eyes is best predicted by alexithymia in both autistic and non-autistic individuals. Information theoretic metrics also revealed differential effects of task on gaze patterns as a function of alexithymia, but not autism. These findings highlight factors underlying atypical emotion processing in autistic individuals, with wide-ranging implications for emotion research.

Keywords: spatiotemporal; eye gaze; eye-tracking; autism; alexithymia; emotion recognition.

1. Introduction

Autism Spectrum Disorder (henceforth ‘autism’) is a condition defined by atypical social interaction and communication, and restricted patterns of thought and behaviour (APA, 2013). The social diagnostic criteria specify a cluster of symptoms¹ that are likely related: a lack of socio-emotional reciprocity, impaired emotion recognition, and reduced eye gaze.

While the exact mechanisms linking these symptoms have not been determined, two hypotheses specify a role for arousal. Under one hypothesis, atypical emotion recognition is a result of active or reflexive avoidance of the eye-region as a result of hyper-arousal induced by direct eye-contact (Kliemann et al., 2012; Hadjikhani et al., 2014). Under the other hypothesis, reduced eye gaze stems from hypo-arousal, resulting in diminished social motivation and orienting responses to social stimuli (Dalton et al., 2005). While there is evidence for both hypotheses (for a review see: Cuve, Gao & Fuse, 2018; Kliemann et al., 2012, Senju et al., 2011), our understanding of how allocation of gaze to faces influences emotion recognition remains far from complete. For instance, previous work demonstrates that an individual’s attention to the eye-region of another’s face is predictive of the degree to which the individual can recognise the other’s emotions (Schurgin et al., 2014). Other studies, however, demonstrate that accurate emotion recognition can occur without overt visual attention to specific face features (Calvo et al., 2014; Peterson & Eckstein, 2012), and with varying patterns of gaze fixations (Yitzak et al., 2020).

It should also be acknowledged that extant studies almost exclusively use static stimuli (c.f. Yitzhak et al., 2020), but recent work highlights the importance of dynamic information as facial expressions evolve over time (Jack et al., 2014). Thus, the predictive value of gaze with

¹ We use the term ‘symptom’ to mirror clinical practice but note that several autism advocates prefer the term ‘traits’ as it avoids equating autism with a disease.

1 respect to emotion recognition may be dependent not only on the allocation of gaze to
2 specific facial features, but also on the spatiotemporal relationships between gaze and the
3 dynamic aspects of facial expressions. Furthermore, the redundancies in information
4 conveyed through the spatiotemporal dynamics of facial expressions are likely to optimise
5 recognition of facial emotion. For example, the kinematics of facial movements may provide
6 additional cues as to the valence and intensity of emotion (Sowden et al., 2020). Such
7 redundancies may explain why allocation of gaze to facial features is not always predictive of
8 emotion recognition, particularly with dynamic stimuli. Importantly, such redundancy is the
9 norm in real-life social interaction, where communication is often multimodal (e.g., involving
10 speech, hand gestures, and gaze direction; Aviezer et al., 2011; Hessels et al., 2020) and
11 benefits from context (Barret et al., 2011).

12 Considering the influential hypotheses concerning the role of atypical eye gaze in emotion
13 recognition in autism (see Hadjikhani, Zurcher, et al., 2017; Kliemann, Dziobek, Hatri,
14 Steimke, & Heekeren, 2010), and the fact that atypical eye gaze is widely regarded as a key
15 diagnostic feature of autism (Senju & Johnson, 2009), it is significant that eye-tracking
16 studies investigating how individuals with autism visually explore emotional faces have
17 produced remarkably mixed results. Although several studies report atypical eye gaze in
18 autism (Hadjikhani, Zurcher, et al., 2017; Kliemann, Dziobek, Hatri, Steimke, & Heekeren,
19 2010; Senju & Johnson, 2009), others do not (Black et al., 2017; Cuve, Gao, & Fuse, 2018;
20 Guillon, Hadjikhani, Baduel, & Rogé, 2014; Kwon, Moore, Barnes, Cha, & Pierce, 2019).
21 Even recent studies incorporating more naturalistic dyadic gaze interactions have produced
22 conflicting results. Some studies found atypical eye gaze only when traditional screen-based
23 measures were used (Grossman, Zane & Micthe, 2019), whereas other studies found a
24 reduction of eye-contact with elevated autistic traits in dyadic gaze interactions (Hessels,
25 Holleman, Cornelissen, Hooge, Kemner, 2018).

There are at least two groups of factors that may explain these inconsistent results. The first relates to individual differences within the autistic population, and the second concerns methodological features relating to task format and how gaze behaviour is operationalised and measured. We discuss these factors below.

1.1. Individual differences

Although heterogeneity within the autistic population is well recognised, appeals to heterogeneity to explain inconsistent results are often vague, with no clear hypothesis about which individual differences contribute to variance in results. However, variability in the socioemotional domain in autism may be systematic, and related to alexithymia, a condition which frequently co-occurs with autism.

The ‘alexithymia hypothesis’ (Bird & Cook, 2013; Brewer, Happé, Cook, & Bird, 2015) suggests that the supposed emotional symptoms of autism are instead due to alexithymia, a condition which co-occurs in approximately 50% of the autistic population (Kinnaird, Stewart, & Tchanturia, 2019). Alexithymia is characterised by the inability to identify and describe one’s own emotions (Berthoz & Hill, 2005). Under the alexithymia hypothesis, inconsistent results when testing various socioemotional abilities in the autism literature are due to sampling variance with respect to alexithymia. Previous data support the alexithymia hypothesis, demonstrating that alexithymia, not autism, predicts reduced empathic brain activity and impaired emotion recognition (Bird et al., 2010; Desai et al., 2019; Heaton et al., 2012; Mul, Stagg, Herbelin, & Aspell, 2018; Trevisan, Bowering, & Birmingham, 2016). Preliminary evidence also points to reduced allocation of gaze to eyes being explained by alexithymia in both autistic (Bird, Press, & Richardson, 2011) and neurotypical individuals (Fujiwara, 2018). Thus, examining effects of autism independent of alexithymia (as is typical

practice for co-occurring depression and anxiety; Cuve et al., 2018; Black et al., 2018), may be crucial in resolving inconsistencies in the literature on autism and eye gaze.

1.2. Methodological features

1.2.1. Spatiotemporal dynamics

In addition to a failure to consider co-occurring alexithymia, there are at least three potentially significant methodological limitations of previous studies. First is the fact that previous studies did not explore the temporal evolution of gaze, instead averaging, or otherwise aggregating, eye gaze across time. This practice does not adequately describe gaze behaviour, which is a dynamic process serving to optimise eye movements for sequential selection of relevant visual information (Kelty-Stephen & Mirman, 2013a; Land, 1999). By reducing such a dynamic process into aggregated measures, studies may fail to capture group differences with respect to the temporal patterns of gaze allocation.

While it is possible that differences between groups in the timecourse of gaze allocation to facial expressions are captured by aggregate metrics, some divergence between aggregate and timecourse metrics is to be expected because dynamic face stimuli convey information which varies in its spatial location over time. Non-linearities in the distribution of gaze allocation are likely in response to more naturalistic and moving stimuli (Tatler et al., 2011; Seedorff, 2019). This is particularly true given the spatiotemporal dynamics of facial expressions, as the diagnosticity of eye and mouth cues for emotion may vary over time, as expressions unfold, and different action units may activate and peak at different (or multiple) timepoints, in a synchronous or asynchronous manner (Jack, Garrod, & Schyns, 2014; Krumhuber & Scherer, 2011). This means that gaze optimised for dynamic emotional facial expressions will likely vary in a non-linear fashion to facial regions over time.

A number of approaches using non-linear modelling (e.g., growth curves) have been proposed to describe the timecourse of gaze allocation to stimuli in other contexts (e.g., word processing in visual world paradigms), under the assumption that the properties of the task, stimuli and/or relevant individual differences (e.g., clinical diagnosis) influence the underlying probability distribution of gaze to regions of interest, and that these distributions provide an estimate of cognitive processing (Barr, 2008; Mirman, Dixon, & Magnuson, 2008; Seedorff, 2018). Importantly, these data (e.g., gaze data in visual world studies) have highlighted that the underlying distribution of gaze is not always well captured in the aggregate (“average”) pattern of gaze data collapsed across time (Kelty-Stephen et al., 2013, Mirman et al., 2008, Seedorff, 2018).

1.2.2. Eye-movement differences and data quality

Eye movements are typically parsed into fixations (to gaze targets) and saccades. Parsing is based on the characteristics of gaze behaviour in neurotypical individuals - not those with autism. Problematically, data suggest that some aspects of eye movement kinematics differ between autistic and neurotypical individuals (Schmitt, Cook, Sweeney, & Mosconi, 2014; Takarae, Minshew, Luna, & Sweeney, 2004). It is also the case that eye movement data from clinical groups are typically noisier, resulting in low precision and robustness (e.g., more missing datapoints) than those from neurotypical individuals (van Renswoud et al., 2018; Hessels et al., 2017; Wass et al., 2013). Individual differences in oculomotor behaviour and the quality of eye-tracking data may contribute to inconsistent parsing of eye movements into fixations and saccades, which may impact the validity of any group-level comparison between a neurotypical and a clinical group.

Even when eye movements are classified correctly, the gaze target must be identified. To do so, areas of the visual scene are determined to contain ‘Areas of Interest’ (AOIs; e.g., the eye-

region of a face). Typically, the experimenter's judgement determines the size and shape of AOIs. This process is subjective and has been shown to be problematic when comparing autistic and neurotypical groups. Hessels and colleagues (Hessels, Kemner, van den Boomen, & Hoge, 2016) showed experimentally that the variability introduced by different AOI production methods can greatly alter the pattern of gaze metrics to face stimuli for atypical groups (e.g. those with autism), more so than for neurotypical individuals. Consequently, variability in gaze parsing and AOI discretization procedures makes published studies in this area difficult to compare and may partly explain the mixed findings.

1.3. Task demands and perceptual priors

It is important to situate any theory of gaze allocation to emotional facial expressions within wider theories of the function of gaze and visual perception. Within wider theories, the important role of top-down factors, particularly perceptual predictions, in modulating gaze behaviour is consistently recognised (e.g., Parr & Friston, 2017; Brook et al., 2019). According to these theories, eye-movements are optimised to reduce sensory uncertainty in order to (dis)confirm perceptual predictions about incoming visual information (Friston, Adams, Perrinet & Breakspear, 2012). Furthermore, beyond salience of the visual scene (a bottom-up factor; Itti & Koch, 2000), the top-down effects of task on gaze behaviour have been recognised for decades and are thought to offer a plausible account of fixation selection (see, e.g., Yarbus, 1967; Tatler et al., 2011). Task demands and goals are thought to determine (and therefore to differentiate) the predictions one makes about upcoming perceptual input, which would be expected to result in different gaze patterns.

Consistent with this idea, gaze behaviour to faces is task-dependent, with task structure and instructions influencing eye gaze more strongly than stimulus-driven factors (Del Bianco, Mazzoni, Bentenuto, & Venuti, 2018; Hessels, Holleman, Kingstone, Hooge, & Kemner, 2019). There is also evidence from neurocomputational models of emotional face processing that humans evaluate the spatiotemporal dynamics of facial expressions with respect to established norms (Furl et al., 2020). In an emotion processing context, these norms can be formalised as perceptual expectations or priors (Jack & Schyns, 2015) which may drive the allocation of gaze and attention to faces.

It is therefore notable that previous mixed findings regarding atypical eye gaze in autism were derived from studies using a variety of tasks. Participants have variously been asked to freely explore (Hadjikhani, Åsberg Johnels, et al., 2017), recognise (Kliemann, Dziobek, Hatri, Baudewig, & Heekeren, 2012) and judge the intensity (Tsang, 2018) of emotional expressions, and have done so to predictable or unpredictable expressions (Subramanian, Shankar, Sebe, & Melcher, 2014). Given the demonstrated dependence of gaze patterns on the task to be performed, thought to be mediated by task-dependent perceptual predictions, it is perhaps unsurprising that different patterns of results have been found across these studies.

The effect of top-down predictions is further complicated in autism by theories suggesting that autistic perception is less influenced by predictions than neurotypical perception (Pellicano & Burr, 2012; Sinha et al., 2014). Under this hypothesis, autistic participants may be expected not to modulate their gaze behaviour based on task requirements or priors about the stimuli, or not to do so to the same degree that neurotypicals do (Król & Król, 2019).

The influence of task and emotion priors on gaze can be estimated using information theory (Shannon, 1948) to quantify the degree of ‘entropy’ or predictability of gaze behaviour (Mirza, Adams, Mathys, & Friston, 2018; Shiferaw, Downey, & Crewther, 2019). If a task

generates strong perceptual predictions (for example if participants know that they will be asked to judge the intensity of a disgust expression (primarily signalled by the mouth), or a fear expression (primarily signalled by the eyes), one would expect a less random pattern of eye gaze than if participants do not know which of these two stimuli they will be asked to judge. However, if autism (or alexithymia) is characterised by a reduced reliance on priors, these effects of task on the predictability of gaze behaviour should be reduced.

1.4. The present study and experimental hypotheses

The overarching goal of this study was to examine whether atypical eye gaze to emotional facial expressions is a product of alexithymia or autism. The primary hypothesis, therefore, is that:

H.1. Any atypical eye gaze to emotional facial expressions will be better explained by alexithymia than autism.

We also aimed to address previous methodological issues in several ways. Perhaps most importantly, was consideration of the temporal dynamics of eye gaze. Describing how gaze to the eye-region of emotional facial expression unfolds over time was a key aim of this study.

The evolution of eye gaze was described by assessing how well gaze behaviour was described by linear, and various types of non-linear orthogonal polynomial terms within Generalised and Linear Mixed Models – GLMMS (Mirman, Yee, Blumstein, & Magnuson, 2011; Seedorff, 2018). With respect to the evolution of eye gaze over time, it was hypothesised that:

H.2. Gaze behaviour to the eye region of emotional facial expressions will be best described by non-linear terms, representing behaviour in which the non-eye regions of the face are explored but where gaze frequently returns to the eyes over the viewing window.

Combining hypotheses 1 and 2, and previous research on the effects of task on gaze behaviour (Tatler, Hayhoe, Land, & Ballard, 2011; Hessels et al., 2019; Król & Król, 2019), leads to hypothesis 3, that:

H.3. The evolution of eye gaze behaviour will be modulated as a function of task and alexithymia and/or autism.

To account for individual differences in data quality and eye movement profiles (which may vary as a function of autism), gaze metrics were derived on a per-participant and per-trial basis using a data-driven adaptive gaze parsing algorithm that accounts for individual differences in eye movements, and variance in data quality (van Renswoude et al., 2018).

Thus if, compared to neurotypical participants, individuals with autism exhibit atypical or idiosyncratic eye movements such that, for example, gaze data shows low robustness (increased data loss) or high levels of noise (low precision), gaze events should still be accurately and reliably classified. Furthermore, AOIs were derived objectively, on a frame-by-frame basis, by adopting a recently-validated automatic AOI specification method (Baltrušaitis & Robinson, 2016; Hessels, Benjamins, Cornelissen, & Hooge, 2018).

To investigate the role of task- and emotion-related priors on gaze behaviour, each participant's gaze was recorded when they were, and were not, cued to the upcoming emotion, and when they were asked to complete a range of tasks (*free-gaze, emotion recognition, and intensity judgements*). It can therefore be determined whether any autism- or alexithymia-related atypicality is dependent upon task parameters, or instead a general feature of gaze behaviour. Two measures of entropy (Stationary Gaze Entropy and Gaze Transition Entropy, Shiferaw et al., 2019) were used to index the complexity of gaze behaviour, as these metrics are thought to reflect the degree of goal-directed visual search prompted by each task (e.g., one might expect more focused, structured, gaze behaviour

when one is cued to the upcoming emotional expression than when not). In relation to the use of priors, we hypothesised that:

H.4. Gaze will be more predictable (as demonstrated by reduced entropy) in the emotion recognition and intensity judgement tasks, and when participants are cued to the upcoming emotion, compared to the free-gaze condition. In common with H.3, any task effect may be reduced in autistic or alexithymic participants.

2. Methods

2.1. Participants

75 participants were recruited from a database of research volunteers and compensated with either an honorarium or course credit. Five participants (3 autistic, 2 neurotypical) were subsequently removed from the study due to a failure to complete the tasks (most commonly because they fell asleep or failed to calibrate properly). Data from 45 neurotypical individuals and 25 individuals diagnosed with autism were therefore included in the final sample (for details see Table 1 and Table S.2. in Supplementary materials). Participants were diagnosed by specialist clinicians all of whom were independent from the research team. Each individual's diagnosis was confirmed using their official diagnosis letter. To the best of our knowledge participants were diagnosed using DSM-V (or DSM-IV) criteria. As part of their inclusion in the participant database used for recruitment in this study, participants were assessed using the original ADOS algorithm administered by a certified professional. As is typical for samples of autistic individuals with a high mean IQ (as in the current sample - see Table 2) and who lead independent lives, not all participants met the cut-off score on the ADOS. Specifically, 7 participants had a total score below 5 on the ADOS, however, all 7 of these participants reached the social cut-off of > 2 , and all scored above the screening cut-off

of 26 on the AQ50 (with 5 of the 7 scoring above the more stringent criterion on this measure, > 32).

2.2.Procedure

Participants completed the questionnaires (see Section 2.3) online before the study. On the day of the study, participants were tested individually in a soundproofed, dimly-lit room, and took short breaks between tasks. After the eye-tracking session participants completed an IQ assessment (Weschler, 1999), after which they were debriefed. Research was conducted in accordance with the revised 2013 Declaration of Helsinki and was approved by the local research ethics committee.

2.2.1. Dynamic Emotional Face Paradigm

The dynamic emotional face paradigm consisted of four conditions in which participants were shown videos of naturalistic dynamic emotional facial expressions from a validated dataset (Yitzhak et al., 2017). Stimuli were displayed full-screen such that the faces occupied approximately 23° vertically and 10° horizontally at a distance of approximately 60 cm. Videos lasted between 8 and 10 seconds, starting with a neutral face that changed to an emotional expression and then returned to neutral in around the last second. 192 trials were presented, 48 in each condition (*free-gaze*, *emotion recognition*, *cued*, and *intensity judgement*), eight of each emotion (neutral, happy, sad, angry, fear, disgust) displayed by four male and four female actors.

1 **Table 1.**

2 Demographic data

Variable	NT		ASD		<i>t</i>	min	max
	<i>n</i> = 45		<i>n</i> = 25				
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>			
TAS20	41.16	14.06	60.44	13.52	5.63***	11	88
AQ28	11.33	4.83	27.24	16.25	4.78***	2	72
DASS21	19.06	13.80	52.08	29.77	5.24***	0	108
ADOS	-		6.92	3.73	-	2	15
IQ	117.76	13.52	121.68	16.49	1.02 ^{ns}	89	150
Age (years)	26.13	6.66	37.68	11.86	4.49***	18	62
<i>Gender</i>							
Male	16		13		$\chi^2=4^{ns}$	-	-
Female	29		11			-	-

3 *Notes.* All t-tests were Bonferroni corrected. * $p < .05$; ** $p < .01$; *** $p < .001$; *ns* = non-

4 significant; NT = neurotypical; ASD = Autism Spectrum Disorder; *M* = Mean; *SD* = Standard
 5 deviation. Note that these analyses do not control for alexithymia.

6 In the *free-gaze* condition, participants were instructed to explore the videos freely as they

7 were presented. This condition is of independent interest, and also serves as a baseline to

8 which the other conditions can be compared. The *emotion recognition* and *intensity*

9 *judgement* conditions involved the participant being informed that they were to recognise the

10 emotion, or judge the intensity of the emotion, respectively. The *cued* condition was the same

11 as the *free-gaze* condition, but participants were informed as to which emotion would be

12 portrayed before the face appeared. Condition order was fixed (*free-gaze*, *emotion*

1 *recognition, cued and intensity judgement*), but trial order was pseudo-randomized per
2 condition for each participant. A delay of 1000 ms \pm 250 ms was used as a jittered inter-trial
3 interval which was converted to the closest delay appropriate for the screen refresh rate
4 (60Hz). This was supplemented by a short system delay of random length at the end of each
5 trial sequence to allow for time-critical logging and trial preparation. This provides for more
6 accurate temporal synchronisation within a trial, with more variable delays between trials.
7 These two processes resulted in a total delay ranging between 1476ms to 1720ms from the
8 end of a trial to the presentation of the next stimulus video. For the *emotion recognition* and
9 *intensity judgement* conditions, 5 practice trials were included. The experiment was
10 programmed and presented in PyGaze (Dalmaijer, Mathôt, & Van der Stigchel, 2014).

11 **2.2.2. Eye-tracking**

12 A Tobii TX300 (Tobii, Sweden) screen-based remote eye-tracker was used with the original
13 screen, sampling at 300Hz and tracking an area of 1920 x 1080 pixels, managed by an
14 experienced operator. Participants were positioned approximately 60 cm from the screen. No
15 chin-rest was used during the study, instead participants were instructed to avoid sudden
16 body and head movements, although they could freely move their eyes while watching the
17 videos. A 5-point calibration was administered at the start of each block and repeated until all
18 points were successfully calibrated according to the eye tracker's default criteria. Validation
19 of the calibration was conducted using the PyGaze routine, and via inspection of the plot of
20 the deviation of gaze to each of the calibrated points. Calibration was accepted if all 5 points
21 had been successfully calibrated, with accuracy $< 1^\circ$. To account for the deterioration of
22 calibration quality expected over time (Holmqvist et al., 2012; Hessels et al, 2017),
23 recalibration was performed after every 20 trials, and additionally when deemed necessary.
24 Recalibration after every 20 trials was based on a pilot experiment showing that participants
25 could complete approximately 20 trials at a time while maintaining an optimal position, with

minimal movement, and without triggering drift correction. Overall, calibration accuracy error was below 1° and precision below 0.3° , and not statistically significantly different as a function of group (See Additional Quality Checks in Supplementary materials).

2.2.3. Eye-tracking data processing

Pre-processing and analysis of the eye-tracking data was completed with custom and adapted processing pipelines in R (R-Core Team, 2013; Dink & Ferguson, 2016). The first 150ms of each trial were excluded from analysis to account for gaze reorientation during screen transitions and fixations initiated before stimulus onset, and the viewing window was locked to 7800ms of full data after re-zeroing. Exclusion of the first 150ms was based on visualisation of the gaze data (both raw and parsed) which indicated consistent rapid reorientation of gaze to facial features after, but not before, this period. This pattern could not have been due to screen change, nor was it due to a fixation cross, since a fixation cross was not presented to limit the central bias induced when viewing stimuli on screens (Hart et al., 2009; Foulsham, Walker & Kingstone, 2011, Tatler, 2007).

Trials and participants with more than 35% of data loss were not analysed. On average, participants contributed 90% of valid data after correction for data loss, and there were no statistically significant group differences in data loss. For fixation analyses, gaze was parsed using a data-driven velocity-based algorithm that accounts for individual differences and quality fluctuations in gaze data (van Renswoude et al., 2018).

2.2.4. Derivation of AOIs

Objective AOIs were derived using an adapted implementation of a recently proposed Limited-Radius Voronoi-tessellation method (LRVT) that builds on open-source facial recognition and landmarking software (Baltrušaitis & Robinson, 2016; Hessels et al., 2018). The method allows identification of the location of facial features in a video over time. AOIs are then created by segmenting the faces using the distances to predefined points indicating distinct features (eyes, mouth, nose). Gaze points were assigned to the AOI that had the smallest Euclidean distance between gaze coordinates and the centre of the AOI, with an AOI radius of approximately 4°; and average eye-to-eye distance of approximately 2°. This method is noise-robust for sparse stimuli like faces and recommended for group comparisons of gaze metrics (Hessels et al., 2018).

2.3. Questionnaire measures

2.3.1. Toronto Alexithymia Scale - TAS20

The TAS-20 was used to measure alexithymia and was scored according to the original norms, with each item rated on a scale from 1 (completely disagree) to 5 (completely agree) which were then summed for a total score (Parker, Taylor, & Bagby, 2003).

2.3.2. Autism Spectrum Quotient – AQ28 and AQ50

To quantify autistic traits, participants completed the AQ28 (Hoekstra et al., 2011). One total score was computed by scoring the 4-point Likert-scale according to the original AQ scoring criteria. The AQ28 was used to quantify autistic traits as recent work suggests it is more consistent with clinical judgment than the AQ50 (Ashwood et al., 2016), and that the AQ50 in its entirety likely contains redundancies that do not necessarily provide improved precision

of measurement (Cuve et al., 2021 *in press*, Lundqvist & Lindner, 2017). AQ50 scores were also available for the autistic participants, and these were used to establish whether autistic participants' scores were above established clinical thresholds.

2.3.3. Depression, Anxiety and Stress Scale – DASS21

To control for any effect of depression and anxiety, these traits were assessed using the DASS21 (Lovibond & Lovibond, 1995). Each item was scored on a Likert-scale from 0 to 3, and a total score was computed by summing all item scores and scaling according to standard scoring methods. DASS scores were used in control analyses.

All questionnaires demonstrated good internal reliability as measured by Cronbach's alpha (.85, .84, and .93, respectively).

2.4. Analysis strategy

The analysis workflow is described in Figure 1. Gaze position data were split into 78, 100ms time bins and the proportion of gaze points within each AOI in each bin was calculated. By using all available gaze points, this approach eliminates the robustness problems with velocity thresholds of parsing algorithms which can affect gaze metrics. To account for the bounded nature of proportional data, these were transformed to empirical logit (elog) and a small epsilon value (.05) added to avoid undefined logarithms (i.e. when the proportion is exactly zero or one).

Data were analysed using GLMMs implemented in lme4 package (Bates, Mächler, Bolker, & Walker, 2014) in R. GLMMs were used rather than other general linear models for several reasons. First, GLMMs are appropriate for autocorrelated data such as the timecourse of gaze

allocation (Mirman et al., 2011; Barr., 2008). Second, GLMMS are more robust to missing data and unbalanced designs (Bates et al., 2014; Jaegar, 2008), which is typical in eye-tracking experiments.

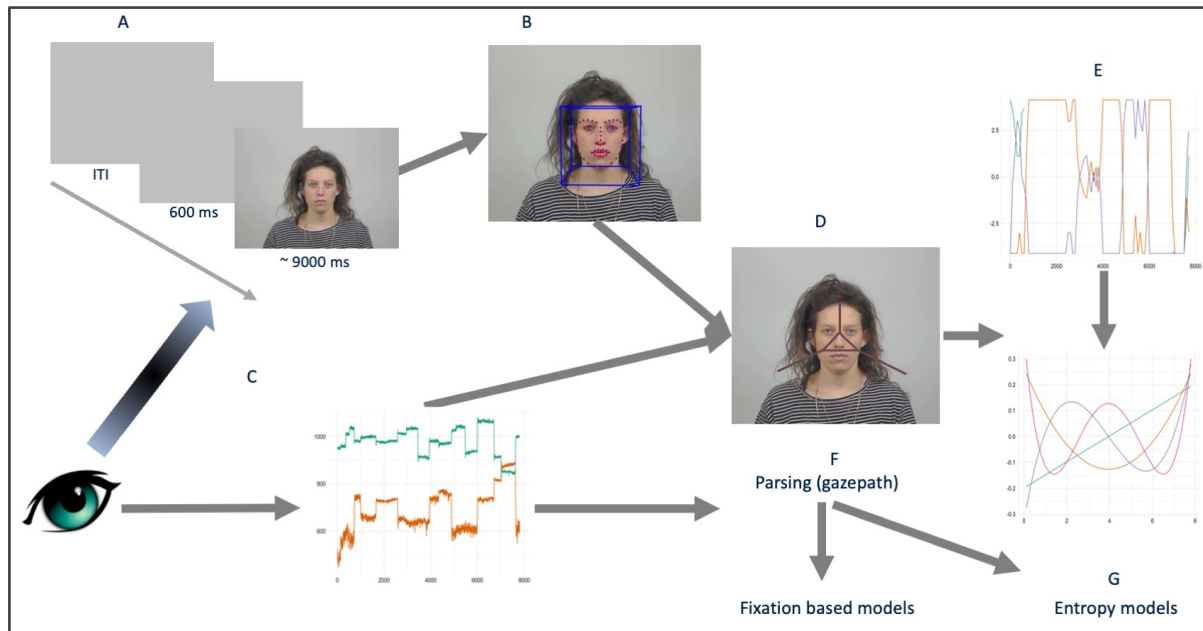


Figure 1. Study design and analysis workflow. A. An example trial from the *free-gaze* condition. B. Sample stimuli with facial landmarks from OpenFace. C. Sample time series of raw eye movements. D. Sample stimuli with superimposed AOI segmentation. E. Sample gaze data for a single trial for an example participant, showing the proportion (eLog) of gaze points in the eye AOI across time (top). Gaze points per AOI were then modelled using the orthogonal polynomials (bottom) in generalised linear mixed models (GLMMs). F. Additional standard analysis of fixation and saccades using data-driven parsing. G. Stationary and Transition Entropy calculation on the parsed gaze.

Third, participant and stimulus effects can be explicitly accounted for. For example, some participants may have a bias to look at the eyes more often than others, and some stimuli may attract eye gaze more strongly than others (Kanana, Bseiso, Ray, Hsiao, Cottrell, 2015, Yitzhak et al., 2020). Finally, most of the assumptions about the distribution and nature of the

residuals which affect the validity and sensitivity of general linear models are often violated in eye-tracking studies. GLMMs have the advantage of allowing for the non-normal distributions that are likely to be encountered with eye-tracking data (Jaegar, 2008; Seedorff, 2018).

2.4.1. Timecourse Analyses

For the timecourse analyses, a method to model the evolution of gaze allocation over time was required that could account for the expected non-linear timecourse of gaze allocation to eyes (Mirman et al., 2008; Seedorff, 2018). Accordingly, orthogonal polynomials, created as powers of the time variable, were used in the GLMM to model the evolution of gaze to AOIs over time. As such an approach has not been used before to analyse autistic gaze behaviour, no firm predictions could be made about which polynomial terms should be included in the model. The simplest terms (linear and quadratic) were therefore included to aid interpretability, and model selection (see below) was also used in order to determine the higher-order polynomial terms to be included before the increase in model complexity was not compensated for by increased predictive power (i.e., before evidence of overfitting was obtained).

Unlike traditional analyses which aggregate gaze behaviour across time, modelling gaze behaviour in this way allows four metrics to be derived. The first is the average behaviour across time (model intercept: for example the average proportion of gaze to the eye-region). The second is the way gaze behaviour changes across time (beta weights for each of the orthogonal polynomial terms: for example, if the beta weight for the linear term is significant it suggests that gaze to eyes can be described as linearly increasing or decreasing over time; if beta weights for both the linear and quadratic terms are significant then it suggests that the change in gaze behaviour across time can be described as a combination of a linear and a U-

shaped pattern. Higher order terms like cubic and quartic, can describe gaze distributions which oscillate more frequently (e.g., as a result of gaze shifts between AOIS), or asymmetries in the curvatures of lower-order shapes (e.g., the quadratic curve).

The third is average differences in gaze behaviour across the time series as a function of autism or alexithymia (beta weights for group main effects, autistic traits or alexithymia). The fourth is how predictors of interest, e.g., autism and alexithymia, alter the evolution of gaze behaviour across time (e.g., beta weights for interactions between group effects and the orthogonal polynomial terms).

2.4.1.1. Time clustering analysis

The polynomial timecourse analysis using GLMMs described above allows significant effects (e.g., significant effects of autism or alexithymia) on the global timecourse of eye gaze to be described but does not allow it to be determined precisely *when* those effects occur or their relative onset. For example, if a significant effect of autism is identified, one does not know whether this effect is largely found at the start of the stimulus video (potentially identifying an atypical orienting response), or whether the effect is sustained throughout the stimulus period. In order to identify when significant effects were observed, a non-parametric cluster-based bootstrapping analysis was performed (of the kind typically used to identify spatiotemporal clusters in EEG data). Specifically, in step 1, the data in each time bin were analysed using GLMMs to identify significant effects at $p < .05$. In step 2, when adjacent time bins were significant, their statistics were summed and they were considered a ‘cluster’, where a cluster reflects a continuous period of time in which significant effects (e.g., of autism or alexithymia) on gaze behaviour were observed. In step 3, the data were then bootstrapped (2000 iterations), such that predictor values (for example diagnostic status) are randomly reassigned and steps 1 and 2 repeated at each iteration, such that a probability

distribution of summed cluster statistics can be created and used to determine the significance of clusters identified with the real data (Maris & Oostenveld, 2007). Such an analysis is appropriate as unlike traditional multiple comparison corrections which are unreasonably conservative for most time-series data, nonparametric clustering has been shown to control for Type I errors while preserving power (Maris & Oostenveld, 2007), and it conserves the temporal effects inherent in the data. Note, however, that this analysis does not obviate the need for the polynomial timecourse GLMM analysis, as that does, and the time clustering analysis does not, allow the shape of gaze evolution to be determined.

2.4.2. Entropy

In addition to standard aggregated analyses across time, the timecourse and time clustering analyses outlined above are essential to address hypotheses 1-3, addressing whether alexithymia or autism is a better predictor of eye gaze (H1), whether the evolution of gaze to the eyes is non-linear (H2), and whether the evolution of eye gaze is affected by task and/or autism or alexithymia (H3). Hypothesis 4 is that gaze will be more predictable (as demonstrated by reduced entropy) in the emotion recognition and intensity judgement tasks, and when participants are cued to the upcoming emotion, compared to the free-gaze condition. In addition, we wanted to investigate whether any task effect may be reduced in autistic or alexithymic participants.

Entropy can be used as a measure of predictability as it reflects the amount of information necessary to describe patterns of gaze behaviour. The more random the pattern, the more information is needed to describe that pattern (i.e., entropy is increased). More predictable, structured, patterns can be described with less information (reduced entropy) and so therefore

more structured and predictable patterns of gaze behaviour in response to the emotion recognition and intensity judgement tasks, and when participants are cued to the upcoming emotion, should be reflected in reduced entropy. Specifically, two measures of entropy were computed: Stationary Gaze Entropy (SGE) and Gaze Transition Entropy (GTE). SGE quantifies the overall spatial dispersion of gaze fixations across the visual scene (and therefore addresses the spatial predictability of gaze behaviour), while GTE provides an estimate of the complexity of gaze transition patterns (and therefore addresses the spatiotemporal predictability of gaze behaviour) and is thought to reflect efficiency in visual scanning behaviour (Shiferaw et al., 2019). SGE was calculated using the formal application of the Shannon equation (Shannon, 1948) as follows:

$$H(x) = - \sum_{i=1}^n (p_i) \log_2(p_i)$$

Where H is the entropy value of a fixation sequence x , i indexes the individual AOI, n is the number of AOIs fixated in a sequence, and p_i is the proportion of fixations in each AOI.

To reflect the fact that longer fixations imply deeper processing of visual information, we used the duration of each fixation to compute the SGE (Hessels et al., 2016).

GTE was computed as follows:

$$H(x) = - \sum_{i=1}^n p_i \sum_{j=1}^n p(i|j) \log_2 p(i|j)$$

Where H is the uncertainty of x when its prior state is known. Thus, the current fixation is best predicted by taking into account the previous fixation location; p_i is the stationary distribution and $p(i|j)$ is the probability of transitioning from i to j AOI (Krejtz, Szmidt, Duchowski, & Krejtz, 2014; Shiferaw et al., 2019). SGE and GTE were normalised by the maximum entropy for all AOIs.

2.4.3. Fitted models

The aggregated gaze, timecourse of gaze data, and gaze entropy were modelled using GLMMs. Several models were built in order to address the study hypotheses and model comparison used to evaluate these models. For example, if one wants to determine whether autism predicts eye gaze one can compare a model of eye gaze which includes all other factors but not autism, with a model including all factors plus autism. If the model including autism fits the data better than the model without (i.e., the addition of autism improves the model fit and does not lead to overfitting), then one can conclude that autism contributes to the prediction of eye gaze and the model parameters can be interpreted. Similarly, if one wants to determine whether autism or alexithymia is a better predictor of eye gaze behaviour then one can compare the fit of a model including autism but not alexithymia, with the fit of a model including alexithymia but not autism (and further compare these models to those containing both autism and alexithymia, and those containing neither autism nor alexithymia).

Fitted models therefore ranged from simpler (e.g., models accounting for random effects only, predicting eye gaze using the orthogonal polynomials only, or orthogonal polynomials plus the effect of the experimental conditions) to more complex models (which included these predictors plus autism and/or alexithymia and interactions between predictors). These models could then be directly contrasted to test whether adding alexithymia or autism improved model fit over simpler models.

To summarise, we tested three groups of statistical models for both the gaze timecourse and entropy:

Group A. Separate models for Autism and Alexithymia:

A.1. Autism Diagnosis Models: Simple models (orthogonal polynomials: linear, quadratic, cubic and quartic for timecourse analyses; condition: free gaze, emotion recognition, intensity judgement, cued) compared to more complex models including autism diagnosis, condition, polynomials (for timecourse analyses) and their interactions.

A.2. Autistic Trait Models: As A.1 but where continuous scores from the AQ-28 - indexing autistic traits - replace the binary autism diagnosis coding.

A.3. Alexithymia models: As A.2 but where alexithymia scores from the TAS-20 replace scores on the AQ-28.

Group B. Joint Autism and Alexithymia Models:

Models in Group B included the crucial predictors of interest as in Group A, but alexithymia was included as a covariate in autism models and vice versa (i.e., all models included autism and alexithymia). Including autism (diagnosis or traits) and alexithymia in the same model is of use as the validity of direct comparisons of models with different fixed effects (as fitted in Group A) is debated. While some fit indices such as AIC and BIC can be used to compare non-nested models fitted with Maximum likelihood (Akaike, 1985), model comparison techniques such as the Likelihood Ratio Test are not valid for non-nested models (Boker et al., 2009; Matuschek et al., 2017).

Group C. Control Models.

This group of models included important control variables that were not the focus of this study (e.g., depression and anxiety, IQ, age, gender) that may still influence gaze and emotion processing, as well a series of sensitivity analyses (e.g., separate analyses by group).

For all models, quasi-maximal random structures were initially fitted. For polynomial models, all models included participant and stimuli random effects on all time terms (see Model equations in Supplementary materials). Convergence issues were solved by simplifying the random structure. This allowed us to fit principled quasi-maximal models while avoiding the incremental computational and power cost of maximal models (Barr, Levy, Scheepers, & Tily, 2013; Bates, Kliegl, Vasishth, & Baayen, 2015). Poisson and binomial distributions were used to fit non-Gaussian count and binary data (e.g., fixation count), or data were log-transformed to meet normality assumptions and correct for exponential distributions (e.g., fixation duration) and additional zero-truncated Poisson models were used to fit zero peaked distributions (e.g., entropy).

2.4.1. Significance testing and model comparison

Model selection was performed by comparing the fitted model of interest, e.g., including alexithymia or autism, to nested models containing all terms, minus these fixed effect(s) of interest via the *anova* function in R. Alexithymia and autism (trait and diagnosis) were also assessed in the same model and the standardised estimates were used to compare which factor (e.g., alexithymia or autism) had the larger influence on gaze. An additional validation used the *step* function from the *lmerTest* package to fit a backwards selection regression and identify eliminated terms. P-values for fitted models were derived using Satterthwaite's approximation (Kuznetsova, Brockhoff, & Christensen, 2017). As part of the model assessment, information criteria (AIC and BIC) were also used to contrast different models (e.g., alexithymia vs. autism models). The full set of comparisons are listed in Table S.3 in Supplementary materials.

2.4.2. Control analyses

Control analyses ensured that data quality or effects of other covariates (e.g., autistic traits, age, IQ, anxiety, ADOS and DASS scores) did not change the results of the main analyses (due to space limitations these are presented in the Supplementary materials - Control and additional analyses).

3. Results

3.1. Aggregated fixation analyses

To enable comparison with previous literature, we present first the standard fixation measures that aggregate over the stimulus viewing window. Two metrics are reported, the number of fixations, and the total duration of fixations.

Gaze distribution to face regions followed expected patterns (see Figure 2 A & B). Specifically, participants spent more time looking at the eyes than the mouth (Estimate = -0.86, SE = 0.18, $p < .001$), and nose (Estimate = -0.61, SE = 0.14, $p < .001$). Similarly, participants fixated the eye regions more times than both the mouth ($Z = -4.78$, $p < .001$) and nose ($Z = -3.53$, $p < .001$). These results are line with other research on face scanning and supported the focus on eye-gaze in subsequent analyses. There was also a slight preference for the nose over the mouth, and interactions with condition; however, to simplify interpretation of results in relation to the research hypotheses, we fit separate models for each region of interest (see below).

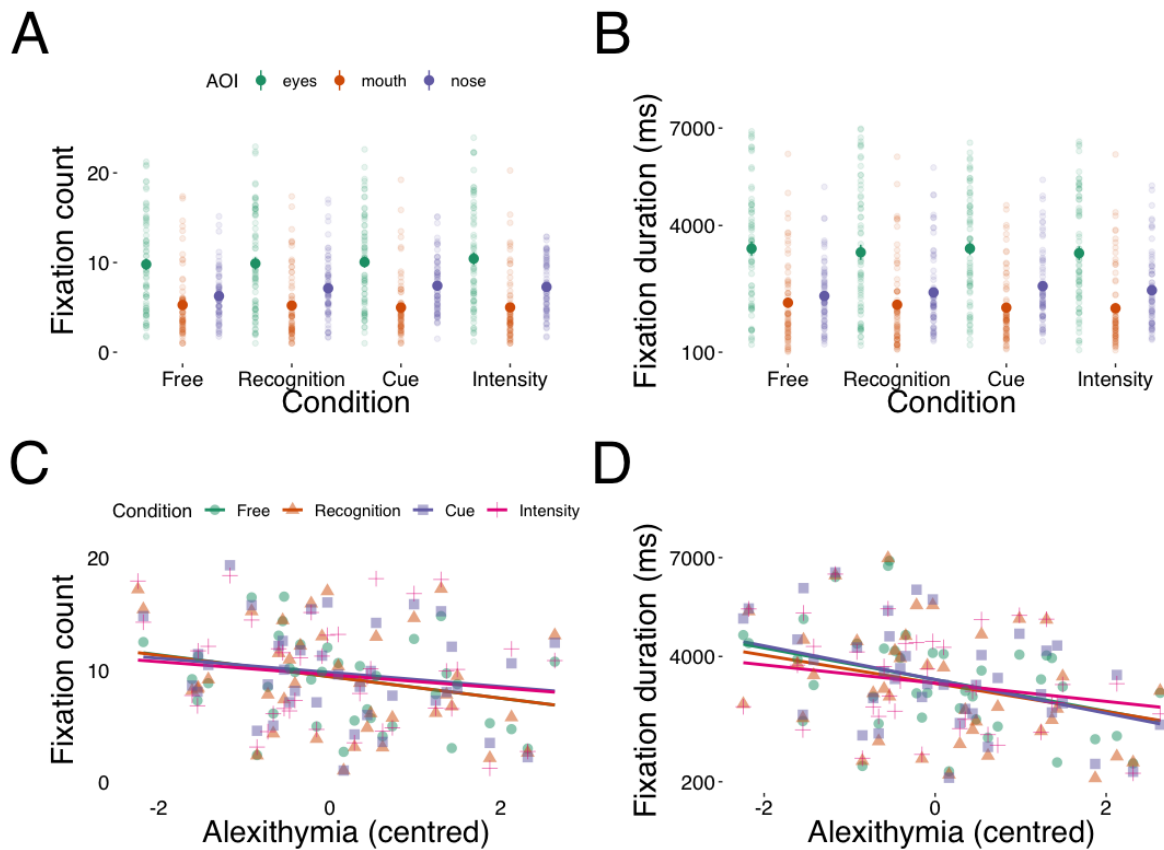


Figure 2. Aggregated fixation count (A) and duration (B) for eyes, mouth and nose.

Participants showed preferential looking to the eyes. B. Fixation count (C) and duration (D) as a function of alexithymia (condition indicated by line colour). Alexithymia predicted both reduced fixation count and reduced duration of eye gaze.

3.1.1. Fixation count to the eyes

3.1.1.1. Free-Gaze condition: effects of alexithymia and autism

Alexithymia outperformed the (null) random effects model ($\chi^2 = 5.98$, $\Delta AIC = 4$, $p < .01$) whereas the autism diagnosis ($\chi^2 = .64$, $\Delta AIC = 2$, $p = .42$), and autistic traits ($\chi^2 = .18$, $\Delta AIC = 2$, $p = .67$) models did not. Additionally, alexithymia emerged as the most predictive term in the joint models ($Z = -2.63$, $p < .01$), in comparison to autism diagnosis ($Z = -0.49$, ns), and autistic traits ($Z = 1.56$, ns). Increasing alexithymia was related to a reduced number of eye fixations during free-gaze (Estimate = $-.17$, $SE = .07$, $p = .01$).

3.1.1.2. Condition effects relative to the free-gaze baseline: effects of alexithymia and autism

For the analysis including all conditions (Figure 2), the alexithymia model outperformed the condition model ($\chi^2 = 13.23$, $\Delta AIC = 123$, $\Delta BIC = 93$, $p < .001$). The autism diagnosis model also provided a better fit to eye fixation data relative to the condition model ($\chi^2 = 125.48$, $\Delta AIC = 112$, $p < .001$) as did the autistic traits model ($\chi^2 = 41.68$, $\Delta AIC = 33$, $p < .001$). Once again, however, the fit indices and the jointly-estimated model indicated a larger influence of alexithymia ($Z = -2.69$, $p < .01$) compared to autism diagnosis ($Z = -.29$, ns) and autistic traits ($Z = .054$, ns). Inspection of the alexithymia model revealed a main effect of increasing alexithymia predicting a reduced number of eye fixations (Estimate = $-.17$, $SE = .06$, $p = .009$).

There was also a significant interaction between alexithymia and condition, characterized by a relative increase in the number of fixations to eyes in the *emotion recognition* (Estimate = $.06$, $SE = .01$, $p < .001$), *cued* (Estimate = $.05$, $SE = .01$, $p < .001$) and *intensity judgement* conditions (Estimate = $.11$, $SE = .009$, $p < .001$; see Figure 2) in relation to the *free-gaze* condition, as alexithymia increased.

Subsequent analyses showed that despite individuals higher in alexithymia demonstrating a reduced number of eye fixations in the free-gaze condition, they do not show a significant reduction in attention to the eyes in the *recognition* (Estimate = $-.14$, $SE = .08$, $p = .06$) *cued* (Estimate = $.11$, $SE = .06$, $p = .07$) and *intensity judgement* conditions (Estimate = $-.08$, $p = .28$). Thus, data from aggregate measures suggest that individuals with alexithymia adapt their gaze behaviour according to the task to be performed.

Overall, traditional analyses of fixation counts support H1; that alexithymia is a better predictor of reduced eye gaze than autism.

3.1.2. Fixation duration

3.1.2.1. Free-gaze condition: effects of alexithymia and autism

Model selection analyses of fixation duration to the eyes in the *free-gaze* condition indicated no significant improvements in model fit for the alexithymia or autism models ($\chi^2 = .09$, $\Delta AIC = -2$, $p = .8$). Therefore, none of the models were interpreted further.

3.1.2.2. Condition effects relative to the free-gaze baseline: effects of alexithymia and autism.

When analysing all conditions, the alexithymia model outperformed the condition model ($\chi^2 = 78.433$, $\Delta AIC = 70$, $p < .001$). The autism diagnosis model also outperformed the condition model ($\chi^2 = 11.871$, $\Delta AIC = 4$, $p < .02$). Importantly the stepwise backwards elimination validation dropped all autism and autistic traits terms but not alexithymia, suggesting a stronger predictive effect of alexithymia and condition on fixation duration to eyes over the other predictors.

The alexithymia model indicated that increased alexithymia is associated with reduced fixation duration to eyes in the *cued* (Estimate = $-.10$, $SE = .01$, $p < .001$) and *intensity judgement* conditions (Estimate = $-.09$, $SE = .01$, $p < .001$), with a non-significant trend for reduced fixation duration to eyes in the *emotion recognition* condition (Estimate = $-.3$, $SE = .01$, $p = .06$). Similar results were obtained when analysing each condition separately.

Alexithymia models also performed better than autism diagnosis and traits models in predicting aggregated fixation metrics to the mouth and nose, yet models accounting for

alexithymia and autism were typically penalised for complexity. This suggests that simpler models including experimental conditions only are sufficient to explain the mouth fixation data (see ‘Aggregated fixation analyses – Mouth AOI’ in Supplementary materials for details).

Overall, analyses of fixation duration data, like fixation count data, support H1 – that alexithymia is a better predictor of eye gaze than autism.

3.2. Timecourse models for eye gaze

The timecourse models of eye gaze data use polynomial regressors locked to the stimulus viewing window to describe the changes in eye gaze proportion across time and how these patterns are impacted by alexithymia and autism (whether measured as the presence or absence of an autism diagnosis or the degree of autistic traits) and conditions. Initially, an analysis of the free-gaze condition alone is presented, which is followed by an analysis of how the pattern of eye gaze changes when comparing each condition to the free-gaze condition. This latter analysis also describes how alexithymia and autism impact the changes in eye gaze patterns as a function of condition. Only critical terms are described in the text below.

3.2.1. Free-gaze condition: Effects of alexithymia and autism

Model comparison indicated that the alexithymia model outperformed the polynomials only (null) model ($\chi^2 = 77.38$, $\Delta\text{AIC} = 67$, $p < .001$), as did the autism (diagnosis) model ($\chi^2 = 14.947$, $\Delta\text{AIC} = 4$, $p = .01$) whereas the autistic traits model did not provide an improved fit over the null model ($\chi^2 = 10.157$, $\Delta\text{AIC} = 0$, $p = .07$). When comparing standardised estimates in a joint model, alexithymia consistently emerged as the most influential predictor (Std. Estimate = $-.23$, Std. SE = $.07$, $p < .001$) compared to autism diagnosis (Std. Estimate =

.09, Std. SE = .08, ns) and autistic traits (Std. Estimate = .11, Std. SE = .07, ns). Similarly, the backwards stepwise selection validation analysis based on AIC eliminated both autism diagnosis and autistic traits and their interactions with polynomial terms, but not alexithymia and interactions with higher order polynomials.

Estimates of the alexithymia model suggested a significant intercept (Estimate = 2.72, SE = .15, $p < .001$) indicating that overall, participants were more likely to look at the eyes than not. There was a significant main effect of alexithymia (Estimate = -.50, SE = .14, $p < .001$), indicating that alexithymia is associated with decreased gaze allocation to the eye region. Alexithymia interacted with higher order polynomials suggesting that temporal evolution of gaze behaviour differs as a function of alexithymia, with highly alexithymic individuals reaching near asymptote after reduced attention to the eyes early in the trial (see Figure 3). Full details and mouth gaze models are presented in Table S.4 in Supplementary materials.

3.2.2. Condition effects relative to the free-gaze baseline: Effects of alexithymia and autism

Timecourse data and model predictions are illustrated in Figure 3. According to all model fit criteria, the alexithymia model significantly outperformed the condition models ($\chi^2 = 2083.3$, $\Delta AIC = 2044$, $p < .001$). The autism model (diagnosis) also provided a better fit than condition models ($\chi^2 = 1146.7$, $\Delta AIC = 1107$, $p < .001$) as did the autistic traits model ($\chi^2 = 412.38$, $\Delta AIC = 373$, $p < .001$). However, when directly contrasted within the same model, standardised estimates for alexithymia effects were significant and consistently larger (Std. Estimate = -.28, Std. SE = .06, $p < .001$) than those for autistic traits (Std Estimate = .07, Std. SE = .07, ns) or autism diagnosis (Std. Estimate = .08, Std. SE = .08, ns).

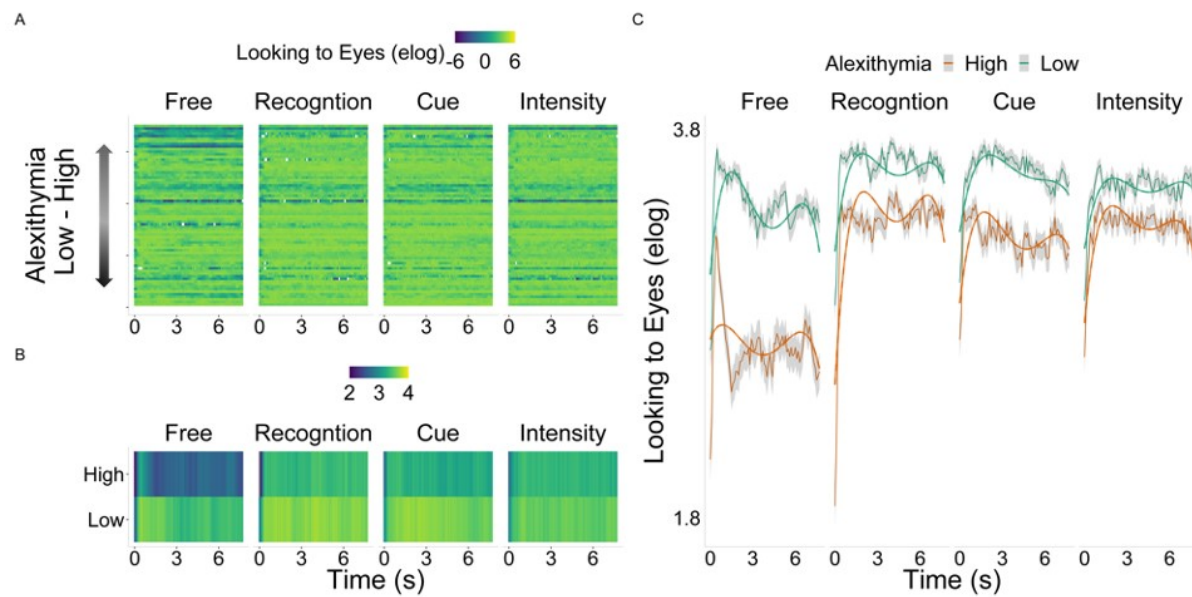


Figure 3. Timecourse analysis. A – B. Raster plots showing reduced gaze to the eye with increasing alexithymia (A) and separated into groups with high and low alexithymic traits (for visualisation only; B); C. Timecourse model for gaze to the eye region. Shaded ribbons represent 95% Confidence Intervals. Solid lines represent predictions obtained from the multilevel polynomial models. The alexithymia model outperforms both the autism diagnosis and autistic traits models in predicting non-linear eye gaze behaviour. The analyses above excluded the first 150 ms of gaze data; the results remained consistent when excluding the first 500 ms or 1000ms. Note that the dichotomisation between high and low alexithymia is for visualisation purposes only, as alexithymia was treated as a continuous predictor.

Similarly, the backwards stepwise selection validation analysis removed the majority of the autism terms and none of the alexithymia terms. These results suggest that a model including alexithymia is a better predictor of eye gaze than autism diagnosis and trait models.

Inspection of the best fitting model (the alexithymia model) revealed a significant interaction between alexithymia and condition for all higher-order time polynomials but not for the

linear term, indicating that alexithymia is related to the condition-specific non-linear trajectory of gaze to the eyes across conditions (See Table S.2). This effect suggests that alexithymia is associated with atypical dynamic gaze exploration of face regions, in particular the eye region. Notably, alexithymia was also related to reduced overall eye gaze across conditions (Estimate = -.48, SE = .10, $p < .001$).

A potential concern that can be visualised in Figure 3 relates to the rapid increase in gaze to the eyes seen at the start of the viewing window. This increase, although an accurate description of participants' eye gaze, likely relates to the onset of the video stimulus and as such may be less representative of real-world viewing behaviour. In terms of analysis, this increase may unnecessarily require that data be fitted by higher order polynomials. Therefore, to guard against the possibility that high-order polynomial terms were improving fit artefactually, additional analyses were conducted excluding the first 500ms and the first 1000ms of gaze data. When the first 500ms of data were excluded it was still the case that models with higher order terms (up to the quartic order) provided significantly better fit to the probability distribution of eye gaze over time compared to just the linear term ($\chi^2 = 974.12$, $\Delta AIC = 954$, $p < .001$) or even the quadratic term ($\chi^2 = 387$, $\Delta AIC = 375$, $p < .001$), and including alexithymia outperformed models with no clinical predictors ($\chi^2 = 1746005$, $AIC = 1746005$, $p < .001$) and with autistic traits ($\Delta AIC = 1743948$) and diagnosis ($\Delta AIC = 904$). Thus, the reported effects remained consistent with those described above, such that alexithymia had significant and large effects on eye-gaze over time compared to smaller and/or non-significant effects of autistic traits or diagnosis (see Table S5 and Figure S3 in Supplementary materials for full details). Excluding the first 1000ms resulted in similar results, with the only notable difference being that the best fitting model was achieved with up to the cubic polynomial, without the quartic term being required.

As a result, we chose to focus on the analyses excluding only the first 150ms. Including as much early data as possible was thought to be important as hypotheses of atypical eye gaze in autism make predictions about gaze orientation and rapid eye avoidance, meaning that early visual attention is theoretically relevant to analysis of eye gaze in autism. While all individuals may show rapid orientation to the eyes, groups of individuals may differ at the rate at which they do so, or at the rate at which they move away from the eyes. A number of published studies in autism use early gaze data, including first fixation (Bours & Bakker, 2018; Kleberg et al., 2017; Kliemann et al., 2012; Madipakkam, Rothkirch, Dziobek, & Sterzer, 2017; Schauder et al., 2019), precisely to test atypical orientation and or eye avoidance. Here, the agreement between the three analyses excluding different amounts of early data provides a sensitivity test of the main findings and suggests that they are robust.

Thus, with respect to the study hypotheses, the timecourse analysis supported H1 in showing that alexithymia explained atypical eye gaze to emotional facial expressions better than autism (either the presence of a diagnosis or autistic traits). H2 was also supported, as the evolution of eye gaze over the stimulus viewing window was non-linear. H3 was also supported for alexithymia: the (non-linear) evolution of eye gaze behaviour was modulated as a function of task, and this task modulation was moderated by alexithymia.

3.2.3. Non-parametric cluster-based analysis

Whereas the previous analyses allow the overall trajectory of gaze to the eyes to be described across time, they do not allow identification of the particular time period(s) over the course of a trial when effects of alexithymia or autism can be seen. To that end, nonparametric time-based cluster analyses were performed on every condition while regressing eye gaze onto

- 1 autism, alexithymia or autistic traits separately, in order to uncover any time-specific effects
- 2 of each factor (see Figure 4).

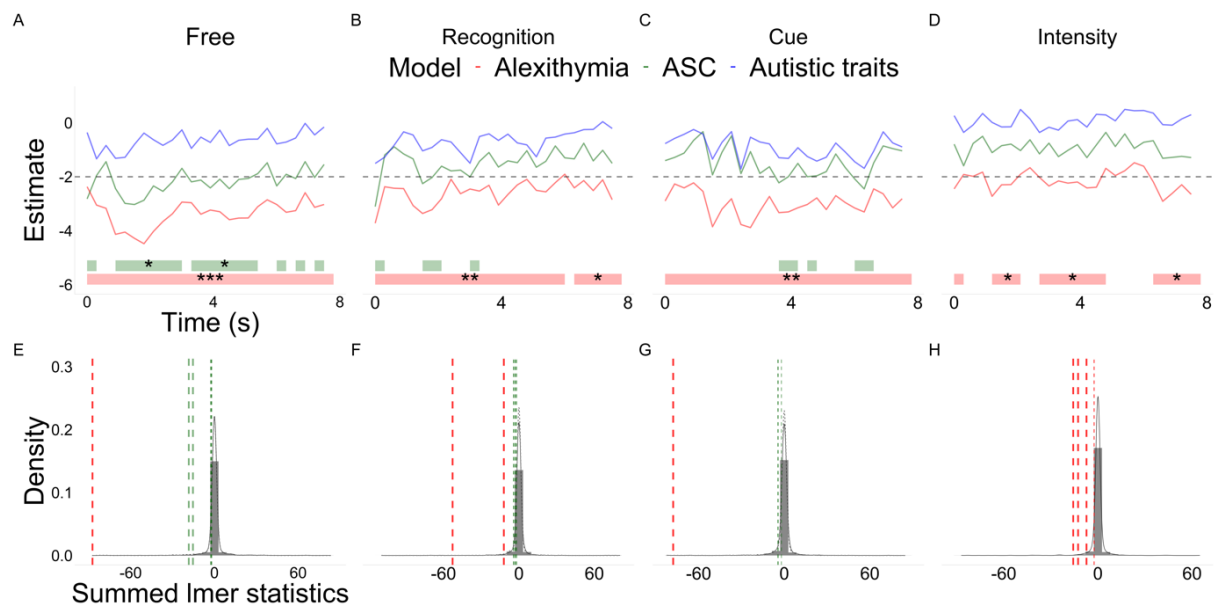


Figure 4. Cluster analysis of timecourse effects. A-D. Shaded areas indicate clusters. If significant, clusters are marked: *** $p < .001$, ** $p < .01$, * $p < .05$. Y axis represent the size of the effect of the standardized predictors on eye gaze. Dashed y intercepts represent lower critical significance limits for estimates from Linear Mixed Models. Alexithymia consistently predicted significant reduced eye-looking behaviour across time and conditions (red shades); E-H. Density plots from the nonparametric cluster bootstrapping. X axis indicate summed estimates for all the time bins in clusters and x intercepts indicate individual clusters coloured by alexithymia (red) and autism diagnosis (green), autistic traits (blue).

In the *free-gaze* condition, there was one cluster spanning the entire stimulus viewing window which was explained by alexithymia. Bootstrapping indicated that this cluster was significant (Cluster_{0-7.8s} Sum Statistic = -87.38, $p < .001$). In contrast, the autism diagnosis model suggested six smaller clusters, of which only two were significant (Cluster_{0.9-3s} Sum

Statistic = -18.39, $p = .03$, Cluster_{3.3-5.4s} Sum statistic = -15.42, $p = .03$). There were no significant clusters for the autistic traits model.

For the *emotion recognition* condition, the alexithymia model accounted for two significant clusters occupying nearly all of the viewing window (Cluster_{0-6s} Sum Statistic = -52.82, $p = .001$; Cluster_{6.3-7.8s} Sum Statistic = -12.03, $p = .03$), demonstrating that alexithymia predicts reduced eye gaze across the duration of the trial. Three small clusters in the first half of the timecourse were attributed to the autism diagnosis model, none of which reached significance when assessed with the bootstrapping analysis (Cluster_{0-0.3s} Sum Statistic = -3.11, $p = .12$; Cluster_{1.5-2.1s} Sum Statistic = -4.28, $p = .10$; Cluster_{3-3.3s} Sum Statistic = -2.00, $p = .23$). No significant time clusters were observed for the autistic traits model.

In the *cued* condition, alexithymia also predicted reduced eye gaze across the timecourse (Cluster_{1-7.8s} Sum Statistic = -77.85, $p = .002$). For the autism diagnosis model, three clusters suggested reduced eye gaze in autism, yet none were significant when assessed with the bootstrapping analysis (Cluster_{3.6-4.2s} Sum Statistic = -4.2, $p = .11$; Cluster_{4.5-4.8s} Sum Statistic = -1.997, $p = .22$; Cluster_{6-6.6s} Sum Statistic = -4.5, $p = .09$). There were no significant clusters for the autistic traits model.

For the *intensity judgement* condition, there were four clusters for the alexithymia model, of which the three largest were significant (Cluster_{1.2-2.1s} Sum Statistic = -7.31, $p = .046$; Cluster_{2.7-4.8s} Sum Statistic = -15.75, $p = .02$; Cluster_{6.2-7.8s} Sum Statistic = -12.66, $p = .03$), with a non-significant early cluster (Cluster_{0-0.3s} Sum Statistic = -2.45, $p = .11$). There were no significant clusters for the autism diagnosis or autistic traits models.

Overall, these analyses highlight that alexithymia is related to consistently reduced gaze to the eyes across conditions and over time (see Figure 4), and therefore support H1; that

alexithymia will explain eye gaze better than autism. Timecourse models predicting gaze to the mouth also favoured alexithymia models over autism diagnosis and autistic traits models. However, simpler models including only the effects of condition and the polynomials were favoured in model selection for the mouth (see ‘Timecourse for the Mouth AOI’ in Supplementary materials for full details).

3.3. Stationary (SGE) and transition (GTE) gaze entropy

Hypothesis 4 stated that gaze will be more predictable (as demonstrated by reduced entropy) in the emotion recognition and intensity judgement tasks, and when participants are cued to the upcoming emotion, compared to the free-gaze condition. Furthermore, in line with the Bayesian hypothesis of autism (Pellicano & Burr, 2012), any task effect may be reduced in autistic (or alexithymic) participants. Accordingly, entropy analyses were used to examine the degree of structure/randomness in the pattern of fixations (SGE) and gaze transitions (GTE), and how the degree of structure was affected by autism, alexithymia, and the experimental conditions. Manipulation checks and additional details for the entropy analyses are provided in the ‘Entropy’ section of the Supplementary materials.

3.3.1. SGE

3.3.1.1. Free-gaze condition: effects of alexithymia and autism

There were no significant effects of any regressor on SGE in the *free-gaze condition*, and no improvement in model fit by the inclusion of alexithymia or autism. None of the models were therefore interpreted further.

3.3.1.2. Condition Effects Relative to the Free-gaze Baseline: Effects of Alexithymia and Autism

When analysing condition effects, the alexithymia model outperformed the condition model ($\chi^2 = 33.75$, $\Delta AIC = 25.7$, $p < .001$) whereas the autistic traits model ($\chi^2 = 5.3211$, $\Delta AIC = 2.7$, ns), and the autism diagnosis model ($\chi^2 = 4.66$, $\Delta AIC = 3.34$, ns) did not. When estimated in a joint model, the backwards stepwise selection validation analysis did not suggest any eliminations, yet this maximal model did not provide any significant improvement in explained variance compared to the alexithymia model, and the fit indices suggested overfitting. The alexithymia model indicated a significant effect of condition. Participants showed less dispersed fixation patterns during the *emotion recognition* (Estimate = $-.007$, $SE = .003$, $p < .05$), *cued* (Estimate = $-.01$, $SE = .003$, $p < .001$), and *intensity judgment* conditions (Estimate = $-.04$, $SE = .003$, $p < .05$). These effects are consistent with top-down priors acting to guide gaze fixations in order to complete the task or confirm the cued emotion. There was also a significant interaction between alexithymia and condition: higher levels of alexithymia predicted increased fixation dispersion during the *cued condition* (Estimate = $.01$, $SE = .003$, $p < .001$; see Figure 5), suggesting weaker modulation of gaze by top-down priors relating to cued emotional expressions in alexithymia. No other alexithymia by condition interactions were significant.

The SGE analysis – providing an index of the predictability of fixations to dynamic face stimuli – supports Hypothesis 4 concerning alexithymia. Gaze was more predictable in the emotion recognition and intensity judgement tasks, and when participants are cued to the upcoming emotion, compared to the free-gaze condition. Furthermore, the effect of task was reduced in alexithymic participants.

3.3.2. GTE

3.3.2.1. Free-gaze condition: effects of alexithymia and autism

The GTE analysis provides an index of the predictability of gaze transitions (as opposed to the spatial predictability of gaze fixations measured by the SGE analysis). As with the SGE analysis, however, condition, alexithymia and autism models did not improve model fit in predicting the complexity of gaze transitions in the *free-gaze* condition. Therefore, these models were not further interpreted.

3.3.2.2. Condition effects relative to the free-gaze baseline: effects of alexithymia and autism

When analysing condition effects, the alexithymia model showed a significant improvement in fit compared to the condition model ($\chi^2 = 39.0$, $\Delta AIC = 31$, $p < .001$). The autism diagnosis model also outperformed the condition model ($\chi^2 = 29.43$, $\Delta AIC = 21.5$, $p < .001$), whereas the autistic traits model did not ($\chi^2 = 2.6$, $\Delta AIC = 5.3$, $p = .6$). A joint estimation of autism diagnosis, autistic traits, and alexithymia effects on eye gaze, did not provide any significant improvement over the alexithymia model and tended to overfit the data according to the BIC ($\chi^2 = 23.23$, $\Delta BIC = 51$, $p < .001$), showing that the alexithymia model was sufficient to predict the complexity of fixation transitions (see Figure 5).

The alexithymia model revealed a significant reduction in GTE in the *emotion recognition* condition (Estimate = $-.03$, SE = $.005$, $p < .001$), and a significant effect of alexithymia in the *emotion recognition* (Estimate = $.01$, SE = $.005$, $p = .01$) *cued* (Estimate = $.03$, SE = $.005$, $p < .001$) and *intensity judgment* conditions (Estimate = $.01$, SE = $.005$, $p = .03$); whereby increasing alexithymia was related to reduced predictability (increased entropy) of gaze transitions in these conditions.

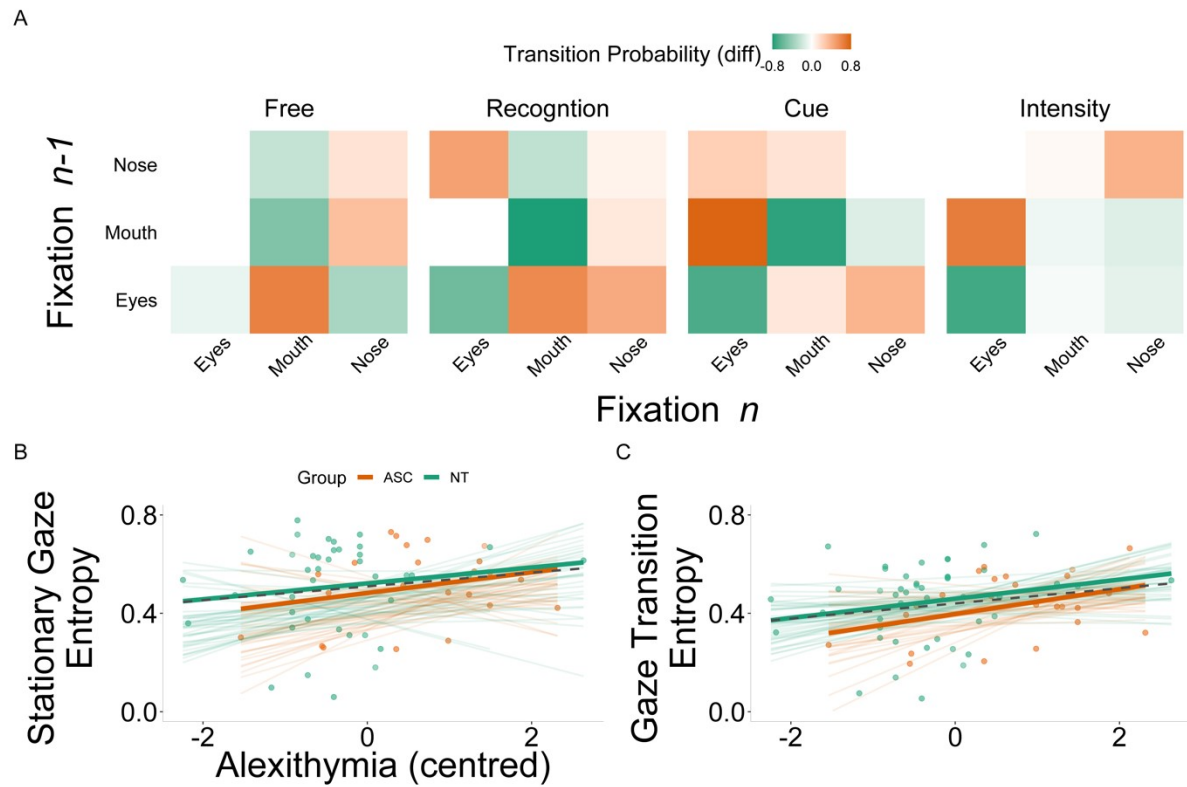


Figure 5. Entropy effects. A. Transition matrices showing the difference in conditional transition probabilities between AOIs (eyes, mouth, nose) as a function of alexithymia (contrasted as high vs. low; median split for visualisation). Positive values indicate increased transition probability for highly alexithymic individuals whereas negative values represent decreased probability of transitions for highly alexithymic individuals. B-C. Scatter plots for linear mixed models showing that increasing alexithymia is associated with increased entropy in both autistic and non-autistic individuals. Dashed line represents global trend line and faded lines illustrate random variability across trials.

Thus, consistent with the entropy analysis of the dispersion of gaze fixations (SGE), the predictability of gaze transitions as a consequence of condition reveals less of an influence of top-down priors relating to task, or knowledge of the upcoming emotional face stimulus, in alexithymic individuals. Thus, both the GTE and SGE data support Hypothesis 4.

3.4. Emotion recognition and gaze

Both autism diagnosis and alexithymia predicted emotion recognition accuracy. Specifically, neurotypical individuals were more accurate than autistic individuals ($Z = -3.79$, $p < .001$), and increasing alexithymic traits predicted poor emotion recognition ($Z = -2.69$, $p = .007$); a similar effect was observed for autistic traits ($Z = -3.24$, $p = .001$), however, in model comparison all of these models had comparable fit and more complex models tended to overfit.

There was however no effect of looking time to eyes on emotion recognition accuracy ($Z = .80$, $p = .4$) nor interactions between looking time and clinical predictors on this measure (all $p > .05$), which was consistent when replacing eyes with nose and mouth looking measures. Similarly, correlations between gaze measures, accuracy and intensity ratings were all below .1 and non-significant (see Table S2 in Supplementary materials). There were also no effects of SGE ($Z = .12$, $p = .9$) or GTE on accuracy ($Z = 1.3$, $p = .19$) nor interactions with clinical predictors (all $p > .05$).

4. Discussion

This study investigated whether autism or alexithymia was the better predictor of eye gaze while individuals with and without autism and alexithymia completed four tasks with dynamic emotional facial expressions. Previous studies addressing eye gaze in autism have aggregated gaze behaviour across time, analysing the number of fixations on, and the total duration of attention to, the eyes (Grynszpan & Nadel, 2014; Hadjikhani, Åsberg Johnels, et al., 2017; Kliemann et al., 2012). Using these standard analyses, the current data indicated that alexithymia was a better predictor than autism of reduced eye gaze to dynamic

1 emotional facial expressions. Furthermore, alexithymia was a better predictor of how these
2 aggregated metrics of overt attention to the eyes changed as a function of condition. The
3 use of an adaptive algorithm (van Renswoude et al., 2018) to parse eye movements into
4 fixations and saccades means it is unlikely that these data can be explained by differences
5 in eye-movements or data quality due to autism or alexithymia.

6 These results are consistent with the only previous study of the impact of alexithymia on
7 attention to the eyes in autism (Bird, Press, & Richardson, 2011) and recent similar
8 observations in non-clinical participants (Fujiwara, 2018; Wiebe, Kersting, & Suslow,
9 2017) and autism (Clin, Maes, Stercq, & Kissine, 2020). These results go significantly
10 beyond these earlier studies however, as previous studies sometimes consisted of small
11 sample sizes (Bird et al., 2011), used hand-drawn AOIs to define gaze to the eyes or used
12 static stimuli, and used standard algorithms developed for neurotypical individuals to parse
13 eye gaze data from autistic individuals into fixations and saccades. These methodological
14 features are limiting for the reasons outlined in the Introduction.

15 Moving beyond traditional gaze metrics, separate analyses incorporated the temporal
16 domain by modelling eye gaze behaviour over time. Three hypotheses were tested using
17 these analyses. H1 stated that alexithymia would be a better predictor of eye gaze than
18 autism. H2 predicted that gaze behaviour to the eye region of emotional facial expressions
19 would evolve in a non-linear fashion over the stimulus viewing window. H3 predicted that
20 the evolution of eye gaze behaviour will be modulated as a function of task and alexithymia
21 and/or autism.

22 Results supported the “alexithymia hypothesis” - demonstrating that alexithymia provides
23 the best explanation of gaze behaviour to the eyes over time, influencing the non-linear
24 changes in eye gaze in both the neurotypical and autistic group, and modulating the effect

1 of task on the evolution of gaze behaviour. The temporal cluster-based analyses were
2 consistent with this, indicating significant effects of alexithymia that persisted across the
3 viewing window across conditions, with very few significant periods in which effects of
4 autism were observed. The persistence of the alexithymia effects mean they are unlikely to
5 reflect atypical reflexive responses or orientation tendencies, and instead likely reflect
6 atypicality in the goal-directed visual exploration of emotional faces in alexithymia.

7 The present study manipulated the task required of participants when presented with the
8 emotional faces. Participants were either free to gaze at the stimuli as they wished when
9 they were unaware of the upcoming emotion, or when they were cued as to the emotion
10 they would see; or they were asked to recognise the emotion or judge the intensity of the
11 emotion. Such manipulations were motivated by previous findings of task-dependant gaze
12 behaviour (Del Bianco et al., 2018; Hessels et al., 2019; Ricciardelli, Carcagno, Vallar, &
13 Bricolo, 2013) and theories suggesting that autistic perception is less affected by priors than
14 neurotypical perception (Pellicano & Burr, 2012). One might therefore have expected
15 individuals with autism to modulate their gaze patterns less when cued to the upcoming
16 emotion, or when required to complete a task, compared to a free-gaze situation. In fact,
17 alexithymia was a better predictor than autism of modulation of attention to the eyes by
18 task.

19 The effect of perceptual priors on gaze was addressed by the fourth hypothesis which stated
20 that gaze will be more predictable (as demonstrated by reduced entropy) in the emotion
21 recognition and intensity judgement tasks, and when participants are cued to the upcoming
22 emotion, compared to the free-gaze condition. Hypothesis 4 also stated that any condition
23 effect may be reduced in autistic or alexithymic participants. Results of the entropy analyses
24 supported Hypothesis 4 in showing reduced entropy (reduced randomness/ increased

1 predictability) in the spatial dispersion of gaze fixations and in gaze transitions in all
2 conditions compared to the free-gaze condition. Furthermore, the effect of the task on entropy
3 was reduced in alexithymia such that individuals with alexithymia showed an increase in
4 entropy (more dispersion and randomness in gaze) during cued conditions. This latter finding
5 is not necessarily inconsistent with other studies showing increased randomness in face
6 scanning in autistic children (Shic, Chawarska, & Bradshaw, 2008; Wang et al., 2020),
7 increased exploratory gaze by autistic individuals (Vettori et al., 2020), and a reduced effect
8 of priors on recurrence of fixations (Król & Król, 2019), as these studies did not account for
9 alexithymia or used non-emotional static visual stimuli.

10 It is worth considering why alexithymia would lead to a reduced effect of condition on gaze
11 entropy, given that the primary prediction relating to condition was an effect of autism, due to
12 theories suggesting that autistic perception is less influenced by predictions than neurotypical
13 perception (Pellicano & Burr, 2012; Sinha et al., 2014). One explanation for the effect of
14 alexithymia on the use of priors is related to imprecise emotion concepts in alexithymia.
15 Previous studies have shown high-level confusion between emotion categories in
16 alexithymia (Brewer, Cook, & Bird, 2016; Cook, Brewer, Shah, & Bird, 2013). Such
17 confusion may mean that alexithymic individuals struggle to individuate emotion categories,
18 which in the context of visual exploration of emotional facial expressions may be reflected in
19 a reduced ability to modulate gaze in response to task demands or to show confirmatory
20 gaze behaviour reflecting predictions about upcoming emotional stimuli.

21 Interestingly, the effect of alexithymia on eye gaze was specific; effects of alexithymia
22 and/or autism on gaze to other face regions were not robust or non-significant. As such,
23 these results reinforce earlier claims of the importance of reduced eye gaze in the autistic
24 population (Kliemann et al., 2010; Stephenson, Luke, & South, 2019), but suggest that the

1 reduced eye gaze to emotional stimuli may be due to co-occurring alexithymia (Bird et al.,
2 2011; Brewer, Cook, Card, Treasure, & Bird, 2015). These results might also be indicative
3 of distinct factors underlying modulation of attention to eyes and mouth. Whereas higher-
4 order emotion processing affects eye gaze, it may be the case that attention to mouth
5 regions is largely dependent on functional requirements of the task, e.g., decoding speech.

6 The current results can inform future research in four ways. First, because the heterogeneity
7 in emotion processing and social attention in autism may be driven by alexithymia,
8 assessment of alexithymia in studies of socioemotional processing and social attention in
9 autism is essential. Second, models of social attention in autism need to incorporate
10 potential causal influences of alexithymia on socioemotional behaviour. Third, looking time
11 measures are likely to underestimate group variability, and for dynamically changing
12 behaviour such as gaze to dynamic expressions, aggregated metrics may not reflect the
13 underlying distribution of visual exploration over time depending on the task (Kelty-
14 Stephen & Mirman, 2013c; Mirman et al., 2008). Describing the temporal dynamics of gaze
15 also offers practical and conceptual advantages over traditional eye-tracking research in
16 autism. For example, data can be analysed without being unreasonably penalised for the
17 multiple comparisons incurred in the use of multiple eye tracking metrics (entry times,
18 fixation duration, dwell), the interpretation of which is often not clear when related to eye
19 gaze hypotheses in autism (Cuve et al., 2018; Hessels, 2020). Fourth, the current results
20 demonstrate that participants modulate their attention to the eyes as a function of the task
21 they were performing. Free-gaze conditions may therefore be more likely to reveal reduced
22 eye attention in the autistic population, as a result of co-occurring alexithymia, than active
23 tasks such as emotion recognition. Conversely, experimental conditions manipulating the
24 effect of priors on gaze may be more sensitive to illustrate atypical modulation of eye gaze

1 which may not be apparent in looking time measures (e.g., when using entropy to measure
2 the complexity of gaze patterns).

3 A limitation of the current study is that it was not optimised to measure the relationship
4 between eye gaze and the accuracy of emotion recognition. Overall, autism and alexithymia
5 were reasonably comparable in how well they predicted emotion recognition accuracy, yet
6 when controlling for alexithymia neither autism diagnosis nor autistic traits had a significant
7 effect on accuracy. Nonetheless, the emotion recognition task was only one of four conditions
8 in the experiment, and only a limited amount of data could be recorded per person in this
9 condition. It is certainly the case that not enough data were recorded to examine how the
10 relationship between attention to the eyes and emotion recognition accuracy might vary
11 depending upon the emotion portrayed. There is, however, consistent evidence from previous
12 studies using carefully matched samples and sensitive emotion recognition tasks that
13 alexithymia is the driver of atypical emotion recognition in both autistic (Bird et al., 2011;
14 Cook et al., 2013; Ola & Gullon-Scott, 2020) and non-clinical volunteers, including
15 correlations with atypical eye gaze (Fujiwara, 2018) and diminished sensitivity to emotion
16 intensity (Starita, Borhani, Bertini, & Scarpazza, 2018). Subsequent studies should therefore
17 explore how autism and alexithymia may impact the relationship between spatio-temporal
18 dynamics of eye gaze and emotion recognition abilities.

19 Finally, it also needs to be acknowledged that the group of autistic individuals who
20 volunteered their participation in this study were not representative of the autistic population
21 as a whole. They were a group of autistic adults with a very high mean IQ, and relatively low
22 levels of overt symptoms (at least when assessed with the ADOS). This experiment therefore
23 needs replicating with a more representative sample of autistic adults and children.

1 **Conclusion**

2 Across different analytical approaches, this study demonstrated that spatiotemporal
3 differences in eye gaze patterns to emotional expressions are best explained by alexithymia
4 rather than autism diagnosis or autistic traits. The findings highlight potential underlying
5 visual processing mechanisms of atypical emotion processing in alexithymia and autism.
6 They echo growing calls for the need to account for the effects of alexithymia when studying
7 emotion processing. They may also go some way towards explaining previous
8 inconsistencies in the literature and may offer a useful model for studying the gaze patterns of
9 atypical groups.

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7 **Author statement**

8 HCC: Conception and design, data acquisition, analysis and interpretation, visualisation,
9 drafting and revising the manuscript.

10 SC: Analysis, visualisation and revising the manuscript.

11 BS: Analysis and revising the manuscript.

12 EI: ADOS interviews and revising the manuscript.

13 CC: Design and revising the manuscript.

14 GB: Conception and design, supervision, interpretation, revising the manuscript.

15

16 **Ethical declarations**

17 All research procedures were in accordance with the revised 2013 Declaration of Helsinki.

18 **Competing interests:** None

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