DEMYSTIFYING EMOTION-PROCESSING: AUTISM, ALEXITHYMIA, AND THE UNDERLYING PSYCHOLOGICAL MECHANISMS

by

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A thesis submitted to the University of Birmingham for the degree of
DOCTOR OF PHILOSOPHY

School of Psychology
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University of Birmingham
December 2023

Abstract

Despite extensive research, the mechanisms underpinning successful emotion recognition remain unclear. Constructionist, template-matching, and signal detection theories illuminate several emotion-related psychological processes that may be involved – namely the conceptualisation, experience, visual representation, and production of emotion – however, this requires empirical verification. Therefore, across the six empirical chapters described here, I developed and applied several novel experimental paradigms to assess the way in which individuals conceptualise, experience, visualise, produce and recognise emotion, and created new mathematically plausible, mechanistic models that shed light on the processes involved in emotion recognition. In doing so, I identified several candidate mechanisms that may underpin the emotion recognition difficulties seen in a range of clinical conditions, including autism spectrum disorder, and I (1) determined whether there are differences between autistic and non-autistic individuals in these emotion-related psychological processes, and (2) ascertained whether differences therein underpin emotion recognition challenges for autistic people.

Ten years ago, it was theorised that the emotion-related difficulties of autistic individuals do not stem from autism per se, but rather alexithymia – a subclinical condition highly prevalent in the autistic population characterised by difficulties identifying and describing emotions. Since its inception, this theory has gained empirical support, with multiple studies documenting that alexithymia, and not autism, is associated with emotion-processing differences. However, to date, this evidence has largely been confined to the domain of emotion recognition. As such, it is unclear whether there are differences between autistic and non-autistic individuals in the conceptualisation, experience, visual representation, and production of emotion, after controlling for alexithymia. Here, I resolved this ambiguity, discerning the explanatory scope of the “alexithymia hypothesis”: there were no differences between autistic and non-autistic individuals in the understanding or differentiation of emotion

concepts (Chapter 6), the precision or differentiation of emotional experiences (Chapter 6), and the speed (Chapter 3) or differentiation of visual emotion representations (Chapter 5), after controlling for alexithymia. Nevertheless, there were differences between groups with respect to the precision of visual representations (Chapter 5), the production of emotional facial expressions (Chapter 7), and recognition of specific emotions (Chapter 2), even after accounting for this confound.

Despite suggestions that autistic individuals adopt alternative strategies to recognise the emotions of others, very few studies have examined mechanistic differences in emotion recognition between autistic and non-autistic people. Therefore, here I aimed to compare the processes involved in emotion recognition for these groups. Across multiple empirical chapters, I identified that there are similarities and differences in the processes implicated in emotion recognition for autistic and non-autistic people (Chapters 4, 5, 6, and 7), with autistic individuals relying on fewer emotion-related psychological processes. By elucidating several candidate mechanisms underpinning superior emotion recognition, my doctoral work paves the way for future supportive interventions to help both autistic and non-autistic individuals to accurately interpret other people's emotions, thus ultimately fostering more successful and fluid social interactions.

Acknowledgements

First and foremost, I would like to thank my wonderful supervisor Jen Cook. I feel incredibly lucky to have been supervised by Jen, who has been a constant source of support, encouragement and wisdom, and dedicated so much time and effort to this work. I am truly grateful for every single interaction, which left me incredibly inspired and energised on countless occasions, and will forever cherish the time spent in Jen's lab. I have no doubt that her optimism, determination, and passion for science will serve as an enduring source of inspiration throughout the rest of my academic career.

I would also like to thank my co-supervisor, Caroline Richards, for warmly welcoming me into her lab, offering me words of reassurance when the imposter syndrome crept in, and for providing invaluable career advice throughout my PhD.

Many thanks also go to my co-supervisor, Sophie Sowden, for her unwavering support over the past four years. From helping me with my application in 2019 to dedicating time to discuss my career in 2023, Sophie's infinite selflessness has been a constant source of inspiration. I am very grateful that I've had the opportunity to work with Sophie on the U21 Autism Research Network, which has been an immensely nourishing, empowering, and (dare I say) fun experience.

Huge thanks go to all members of the Cook Lab, past and present: Jen Cook, Alicia Rybicki, Sophie Sowden, Bianca Schuster, Lydia Hickman, Dagmar Fraser, Hélio Clemente Cuve, Molly Gracey, Holly O'Donoghue, Jelka Stojanov, Carmen Kraaijkamp, Mike Gachomba, and honorary member Poppy Aves. I am really grateful that I've had the opportunity to get to know, and work with, such a great bunch of people. I will certainly miss our dinners, zoom D&D sessions, and karaoke nights – how will I go without hearing your angelic vocals? Special thanks go to Lydia for being the Gabriella to my Troy, and for giving me her unwavering support as we navigated the highs and lows of our respective PhDs – I look forward to more lengthy voice notes as we embark on the next chapter of our lives.

I would also like to thank the Medical Research Council for supporting the completion of this work. Special thanks also go to the research participants who took part in these empirical studies – none of this research would have been possible without you!

Finally, I would like to thank my beloved family for their unconditional love and support, and for instilling the idea that there's no ceiling on what we can achieve. Hannah, thank you for being constant a source of acceptance and inspiration – I couldn't ask for a better big sister. To my parents, I cannot thank you enough for everything you've done for me, from welcoming me back home while I've been writing this thesis to reading to me when I was younger – maybe that paid off after all.

About this thesis

This thesis comprises six empirical chapters. Four of these empirical chapters are exact copies of published journal articles (Chapters 2, 3, 4, and 5), and two are exact copies of pre-prints (Chapters 6 and 7) that are under review at journals, with two exceptions. Firstly, for reader's ease, repeated methodological information, for example regarding task descriptions, is redacted where applicable. For example, since our EmoMap and ExpressionMap tasks are introduced in Chapter 4, we redact the descriptions of these tasks in Chapters 5 and 6. Secondly, the headings, subheadings and references have been reformatted to be a consistent style throughout. In addition to these empirical chapters, this thesis includes a general introduction, which provides an overview of the literature, and a general discussion, which places our finding within the literature and discusses strengths, limitations, and future directions.

Author contributions for each empirical chapter

Chapter 2: C.T.K* and J.L.C conceptualised and designed the study. C.T.K* reprogrammed the task to facilitate online testing and collected the data. C.T.K*, S.S. and D.F. processed the data. C.T.K* analysed the data and wrote an initial draft. C.T.K*, S.S. and J.L.C. reviewed and edited the initial draft. Supervision was conducted by S.S. and J.L.C. All authors reviewed and provided feedback on the draft and approved the submitted manuscript.

Chapter 3: C.T.K* and J.L.C conceptualised and designed the study. C.T.K* programmed the tasks, collected, processed and analysed the data, and wrote the initial draft. C.T.K* and J.L.C reviewed and edited the initial draft. Supervision was conducted by J.L.C. Both authors reviewed and provided feedback on the draft and approved the submitted manuscript.

Chapter 4: C.T.K* and J.L.C conceptualised and designed the study. C.T.K* programmed the tasks, collected, processed and analysed the data, and wrote an initial draft. C.T.K* and J.L.C reviewed and edited the initial draft. Supervision was conducted by J.L.C. Both authors reviewed and provided feedback on the draft and approved the submitted manuscript.

Chapter 5: C.T.K* and J.L.C conceptualised and designed the study. C.T.K* and E.I. collected the data. C.T.K* processed and analysed the data, and wrote an initial draft. C.T.K* and J.L.C reviewed and edited the initial draft. Supervision was conducted by J.L.C. All authors reviewed and provided feedback on the draft and approved the submitted manuscript.

Chapter 6: C.T.K* and J.L.C conceptualised and designed the study. C.T.K* and C.K. collected, processed and analysed the data. C.T.K* wrote an initial draft. C.T.K* and J.L.C reviewed and edited the initial draft. Supervision was conducted by J.L.C. All authors reviewed and provided feedback on the draft and approved the submitted manuscript.

Chapter 7: C.T.K* and S.S. designed the study. C.T.K* collected the data, processed and analysed the data, and wrote an initial draft. H.O.D assisted with data-processing. C.T.K* and J.L.C reviewed and edited the initial draft. Supervision was conducted by J.L.C. All authors reviewed and provided feedback on the draft and approved the submitted manuscript.

*denotes the author of this thesis

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List of abbreviations

Analysis of variance (ANOVA)

Autism Diagnostic Observation Schedule, version 2 (ADOS-2)

Autism Spectrum Disorder (ASD)

Autism Quotient (AQ)

Autonomic nervous system (ANS)

Bermond Vorst Alexithymia Questionnaire (BVAQ)

Birmingham Psychology Autism Research Team (B-PART)

Communication subscale of the AQ (AQ C)

Dependent variable (DV)

Difficulty identifying feelings subscale of the TAS-20 (TAS DIF)

Facial electromyography (fEMG)

Frames per second (FPS)

Intelligence Quotient (IQ)

Interquartile range (IQR)

Intra-class correlation coefficients (ICCs)

Matrix Reasoning Item Bank (MaRs-IB)

Mean importance scores (MIS)

Multidimensional scaling (MDS)

Non-verbal reasoning (NVR)

Perth Alexithymia Questionnaire (PAQ)

Point-light face (PLF)

Science, Technology, Engineering and Mathematics (STEM)

Standard error of the mean (SEM)

Signal detection theory (SDT)

Toronto Alexithymia Scale (TAS-20)

Wechsler Abbreviated Scale of Intelligence (WASI)

95% Confidence Intervals (95%CI)

Chapter 1: General Introduction

1.1. Overview

My doctoral work featured two primary aims: (1) to elucidate the mechanisms involved in, and build empirical models of, autistic[a] and non-autistic emotion recognition, and (2) to examine whether there are differences between autistic and non-autistic individuals in the conceptualisation, experience, visual representation, production, and recognition of emotion, after controlling for alexithymia – an important confound. In doing so, I hoped to elaborate on existing theories pertaining to the experience and recognition of emotion, and expand upon current knowledge regarding the origin of putative socio-emotional difficulties for autistic people. As such, in the current Chapter, I first synthesise the evidence concerning theories of human emotion and emotion recognition. In doing so, I highlight several candidate mechanisms that may contribute to emotion recognition difficulties in autism spectrum disorders – the precision and differentiation of semantic emotion concepts, emotional experiences, visual emotion representations, and emotional facial expressions. Second, I consider autism, social cognition, and emotion-processing, with a specific focus on these factors. Throughout, I discuss a possible role for alexithymia, address shortcomings of previous research, and highlight gaps in the literature.

1.2. Theories of human emotion

Humans are emotional creatures. Emotions shape our relationships throughout our lives[1,2], influence attention, memory and decision making[3-6], and contribute to our physical

[a] In line with language preferences of the majority of the autistic community[586,587], identity-first language is used throughout.

health[7] and psychological wellbeing[8]. Due to its role in numerous aspects of our lives, it is unsurprising that emotion has been a topic of scientific enquiry for over 150 years[9-11]. However, despite extensive research by psychologists, anthropologists and sociologists over this period, researchers still cannot agree on the definition of emotion, and the process by which it is experienced (see [12-14]). For the purpose of this thesis, I consider emotions to be short-lived psychological phenomena that are constructed when the brain makes predictions about our neurophysiological state based on previously acquired knowledge and experiences (taking influence from constructionist theories[14]; see below).

Perhaps, the earliest theory of emotion was devised by Charles Darwin in *The Expression of the Emotions in Man and Animals*[9]. In this book (and others), Darwin proposed that facial movements, gestures, and physiological changes that accompany expressed emotions are largely universal, instinctive, and inherited, as such behavioural modifications were adaptive in our early evolutionary environment[9,15]. These ideas were highly influential in shaping contemporary theories of emotion.

Approximately ten years later, William James and Carl Lange proposed their theory (James-Lange theory[10]), delineating the process by which emotion is experienced. According to this theory, a stimulus activates the sensory cortex which directly evokes physiological and/or motor responses[10]. Following this, the feedback from these responses travels back to the sensory cortex where it generates an experience of emotion[10]. In essence, this theory proposes that the conscious awareness of a physical sensation results in (and equates to) an experience of emotion[10]. To illustrate this idea, imagine that you encounter a threat in your environment, for example a venomous snake. Upon detecting this threat, your sympathetic nervous system initiates physiological arousal, making your heart race. Under the James-Lange theory, you would experience ‘fear’ after recognising these physiological changes in your body. According to James[10], each specific emotion has its own unique set of physiological and neural responses; the response signature associated with excitement differs from that of fear, which differs from that of anger.

Although this theory was prominent during its time, it was criticised by Walter Cannon for several reasons. Firstly, Cannon[11] highlighted that each emotion does not have its own unique response signature as the physiological responses accompanying distinct emotions lack specificity (e.g., fear and excitement are both associated with elevated heart rate). Second, Cannon[11] argued that artificial elicitation of physical arousal, for example via injections of adrenaline, does not generate real emotional experiences, as would be predicted by James' account. Finally, Cannon[11] noted that disrupting feedback (e.g., via disconnection of the central nervous system from peripheral organs), does not eliminate emotion, suggesting feedback between these systems is not integral to affective experiences. On the theoretical side, James[10] reduced emotions to experiences of bodily responses and thus did not account for the fact that emotions can have a cognitive component, being intentional and object-directed[16-18].

Mitigating some of these limitations, Cannon and Bard came up with their own theory (Canon-Bard theory[11]). They proposed that physiological arousal and the experience of emotion occur simultaneously, yet independently[11]. According to this theory, when you see the venomous snake, you feel fear at the exact same time that your sympathetic nervous system prepares your fight or flight response[11]. That is, the emotional experience of *fear* is separate and independent of the physiological arousal, even though they co-occur. Critics of this theory argue that the experience of emotion cannot be separated entirely from the physiological component[19].

With the growth of cognitive psychology in the 1950s, cognitive theories of emotion became the prevailing viewpoint. One highly influential cognitive theory is the Two-Factor

Theory, as proposed by Schachter and Singer in 1962[20,21]. This theory combines elements of both previous theories and addresses their main limitations[12]. As the name suggests, this theory proposes that there are two steps to emotion: first, an individual experiences physiological arousal, and second the individual *consciously* interprets the response based on the situational context[20,21]. Revisiting the previous example, the two-factor theory asserts that the snake evokes activation of the sympathetic nervous system which is subsequently labelled as fear given the context. Importantly, this theory can allow for similar autonomic nervous system (ANS) responses for different emotions (as similar ANS responses could be interpreted differently based on context), thus mitigating the limitations of James-Lange[12]. Concurrently, this theory maintains the connection between physiological reactions and emotional experiences, thus addressing the pitfalls of Canon-Bard[22].

Schachter and Singer[19] found support for their theory by demonstrating that injections of adrenaline (causing physical arousal) resulted in experiences of joy or anger depending on the presence of a happy or angry bystander. Thus, the researchers showed that the same physiological experience can be interpreted differently according to the situational context. Although this theory was highly influential and supported by some empirical work, a number of critics challenged it on theoretical and empirical grounds (see[22-24]). For example, Zajonc[23] disagreed with the idea that conscious appraisal is imperative for the experience of emotion. Following this, studies showed that repeated exposure to a stimulus that was presented subliminally (such that the stimulus could not be consciously identified) led to increased liking of such a stimulus[24]. This led the authors to suggest that *unconscious* appraisals (and not just conscious ones) may play a role in affective experience. Such findings support the central ideas discussed in appraisal theories.

Appraisal theories of emotion (e.g., [25-33]) retained Schacter's[20,21] assertion that cognition is an antecedent to emotion, but argued that the cognitive component is primarily unconscious (see [12] for a full discussion appraisal theories). Madga Arnold pioneered this category of emotion theory in 1960, coining the term 'appraisal' to mean the cognitive act of evaluating a situation[25]. These theories differ from the two-factor theories by placing the cognitive component directly following the onset of the stimulus and prior to the bodily responses. According to some appraisal theories, following the introduction of a stimulus, an individual makes an unconscious appraisal (evaluating whether a situation is positive or negative), which results in an action tendency (i.e., approach or avoid) and a physiological and/or motor response, which is then consciously labelled as a particular emotion (see [12]). Thus, such theories introduce an *unconscious* attribution process, and shift Schacter's *conscious* attribution to the end of the emotional episode. Returning to our example, after perceiving the snake, you may unconsciously appraise that the situation is dangerous, causing your heart to race (i.e., physiological changes), which you then consciously label as fear.

Most recently, constructionist theories of emotion, such as the Conceptual Act Model[14,34-40] have gained traction. These theories, first proposed by Lisa Feldman Barrett, postulate that emotions are constructed, automatically, from two basic psychological primitives that influence and constrain each other: (1) a basic neurophysiological system that produces variation in core affect (i.e., arousal and valence[41]), and (2) a conceptual system for emotion (i.e., one's knowledge about emotion)[14]. These psychological primitives will be discussed in greater detail below.

The first psychological primitive that contributes to the construction of emotion is a *core affect system*[14], which comprises neurophysiological states that can be defined in terms of valence (i.e., pleasantness versus unpleasantness) and arousal (see [42,43] for reviews). The purpose of this system is to integrate sensory signals from the environment (e.g., the presence of a venomous snake) with interoceptive and homeostatic bodily signals to create a mental state that allows us to predict threat and reward, and thus safely navigate the world. Essentially, core affect can be seen as a neurophysiological barometer which reflects an individual's response to changing events in their environment[14].

According to the Conceptual Act Model, the experience of feeling an emotion, or perceiving it in others, also relies on the involvement of a second psychological primitive – our conceptual emotion knowledge (i.e., what we "know" about emotion)[14]. According to this model, we possess a conceptual system that houses all the knowledge we have acquired via previous experiences – the bodily sensations, semantic meanings, motor responses (e.g., facial expressions), and contexts (amongst others) that we associate with distinct emotions[14,44]. By accessing the knowledge in this conceptual system, we are able to make sense of, and categorise, core affect, thus producing experiences of "anger", "happiness" or "sadness" (or whatever categories exist in one's conceptual landscape)[14].

Such categorisation processes are fundamental cognitive activities that allow the brain to make a prediction about the meaning of sensory information[14,45, 46]. Categorizing something renders it meaningful, determining what something is, why it is, and what to do with it[14]. To explain this categorisation process, Barrett draws an analogy between categorising emotions and categorising colours[46]. Although the retina registers light across a continuous spectrum of wavelengths, people perceive distinct categories of colour – "red", "yellow", "green" – due to the previously acquired conceptual knowledge. According to her theory, the same happens with emotion[14,46]; the act of categorizing core affect can be considered as similar to figure-ground segregation[47,48], wherein emotional experiences emerge as separate events from ongoing changes in core affect. In essence, emotion concepts transform ongoing changes in arousal and valence into interpretable and meaningful experiences (e.g., “happiness").

But what exactly are emotion concepts, and how do they form? According to Barrett[14,46] concepts are embodied (e.g., [49,50]), multimodal (e.g., [14,44]), representations of emotions that are acquired through experience. Barret[14,46] contends that an emotion concept, like *happiness*, evolves as sensory, neurophysiological, and motor information is integrated across numerous instances where *happiness* is labelled. That is, sensory cues from your environment (e.g., visual or auditory information about your interaction partner), neurophysiological information about your core affective state (e.g., current homeostatic state), motor responses (e.g., facial movements, loudness or tone of voice), and so on, all bind together with the label “happiness” (which could be provided by yourself or others) to form a singular instance of happiness[14]. Across instances, the multimodal information is integrated, and thus the conceptual knowledge about happiness accumulates[14]. According to this theory, large collections of information reside within your concepts, and this information can be retrieved and combined in diverse and flexible ways to produce an experience of emotion[14].When our conceptual knowledge about happiness is primed, for example by the sensory environment (e.g., hearing the voice of your favourite comedian), a motor response (e.g., smile), and/or core affect (e.g., positive valence, high arousal), the concept is activated, thus encouraging us to experience or perceive “happiness” in that particular situation.

Central to this model is the idea that emotion concepts shape both experiences (i.e., inferences about how oneself is feeling) and perceptions of emotion (i.e., inferences about how others are feeling[14, 51-56]). Under this theory, individuals with lower access to emotion concepts should have greater difficulties interpreting their own and others’ emotions. One approach to testing this hypothesis is to assess the experience or perception of emotion in those who naturally lack access to concepts, for example those with semantic dementia[46]. These individuals typically have permanent brain lesions which impair their ability to remember words and concepts, including those for emotion[46]. One study involving these individuals found that although they were able to classify emotional facial expressions as 'pleasant' and 'unpleasant' (i.e., could make judgements based on core affect), they were unable to categorise them as discrete emotions like anger or sadness (even when such judgements did not require the use of emotion words[57]). Such evidence suggests that emotion conceptual knowledge (which the patients could not access) transforms perceptions of affect into experiences of discrete emotions.

Another approach is to experimentally restrict access to emotion concepts, for example by semantic satiation, and assess the consequences for emotion perception[14,46]. In semantic satiation experiments, participants repeatedly say a category word until it becomes just a sound that is mentally disconnected from its meaning[14]. Following this, participants have to judge whether a stimulus is a member of the repeated category[14]. In such experiments, relative to repeating an emotion word a few times (i.e., low semantic satiation), repeating it numerous times (i.e., high semantic satiation), led to slower and less accurate judgements of whether a subsequent facial expression matched the repeated word[58,59]. In later studies, after undergoing semantic satiation, participants were presented with two pictures of emotional facial expressions and were required to judge whether they were displaying the same emotion[58]. This allowed the researchers to examine how temporarily restricting access to a concept influences perception when it is not necessary to label the face stimuli verbally. This work identified that semantic satiation led to slower ability to determine whether two facial expressions matched each other or not[58]. Thus, rendering the emotion concept less accessible led to difficulties with emotion perception, supporting the role of concepts in the recognition of others' emotions.

Thus far, the extant literature has primarily focused on empirically demonstrating that the *accessibility* of emotion concepts influences emotion perception (see [46] for a full discussion). However, according to constructionist theories[14,51], the *differentiation* of such concepts should also play a role. From a developmental standpoint, these theories suggest that across the lifespan, emotion concepts evolve from a positive-negative dichotomy into more differentiated multidimensional representations (i.e., based on arousal, context, motor responses, semantic meanings etc.) via the accumulation of conceptual emotion knowledge (through experience), thus producing concomitant shifts in the experience and perception of emotion[51]. Essentially, an individual with a greater range of emotion concepts will have a more precise and differentiated framework for categorizing their own and others' emotions. If, for example, your concepts for anger and sadness are overlapping – perhaps they are associated with similar core affect, motor responses (e.g., facial expression) or contexts, or have a similar semantic meaning to you – it will be difficult to distinguish whether you and others are feeling angry or sad. If, on the other hand, your concepts are differentiated for highly similar emotions, such as irritation and frustration, you are likely to be able to categorise yours and others' emotions precisely as such. Nevertheless, although existing theories suggest that the differentiation of emotion concepts will play a role in the experience and recognition of emotion, research is yet to test this idea.

Interwoven into the fabric of these past theories is the *function* of emotion. In most early work, the dominant view was that emotions primarily serve an adaptive role, facilitating survival in response to human predicaments such as threat[60]. Under this framework, experiencing the emotion *fear* in response to predators or enemies is adaptive as it results in individuals being highly vigilant or avoidant, thus improving the probability that the individual will escape such a threat (see [60]). Such work has primarily been shaped by biological and evolutionary perspectives, and has mostly ignored the social function of emotion[61]. However, more recent theories have argued that human emotions have developed and are experienced, expressed, and regulated through others and with others (e.g., see [2,61-63]) Thus, unsurprisingly, in addition to emotions serving an adaptive function (e.g., facilitating appropriate responses for survival), many researchers argue that emotions possess a social function – allowing us to communicate our needs, intentions, desired courses of action, and role-related expectation and behaviours[63-66], offering opportunities for shared affective experiences (see [67]), and thus facilitating the formation and maintenance of social relations[68-74]. Some have even gone as far to say emotions are imperative for "social survival" (e.g., [75]) – for building social ties and to overcome social problems including loss of power and status, or exclusion (e.g.,[76-79]). Thus, emotions can be seen as important tools for social communication.

1.3. Emotions as tools for social communication

Humans are highly social beings, deeply embedded into a world where social information is ubiquitous in everyday life. One of the richest sources of this social information is the face, from which observers can readily make a number of inferences[80] – for example about identity[81-84], gender/sex[85-87], ethnicity[88-90], physical health[91,92], attractiveness[93,94], personality[95-97], and emotional state [8, 98-101]. The latter of these has attracted a large amount of interest for over a century, perhaps because the ability to effectively convey emotions is important for both expressing one's intentions and basic needs, and also for ensuring the success and fluidity of social interactions (e.g.,[60-62,102]). In scenarios where individuals can read the expression of their interaction partner, they are able to respond in an adaptive and/or socially appropriate manner. For example, successful conveyance of sadness (e.g., a downturned mouth and eyes filling with tears) may elicit reassurance, words of comfort, or a hug from another person (see [103]). Successfully communicating threat, aggression or submission, on the other hand, prevents potentially harmful encounters, thus benefitting all participants in the interaction[104]. In contrast, a breakdown in communication – for example difficulties in conveying or recognising emotional signals– can significantly damage social relations, precipitating increased risk of social isolation[105-107], or even physical or mental harm[80,104].

An important question is therefore where do these breakdowns in communication come from? In other words, why is it that some individuals struggle to recognise the emotions of other people, or convey their own emotions? To start to answer this question, it is useful to consider modern theories of emotion recognition.

1.3.1. Theories of emotion recognition

At present, the most widely accepted theories of emotion recognition are template matching models. Under these theories, the emotional facial expressions that we encounter are compared with stored templates (i.e., imagined visual representations of emotional expressions), which allows us to identify the displayed emotion[108-111]. To fully explain the process by which template matching is theorised to occur, and the relevant empirical support, it is necessary to draw on the core principles of 'face-space'[112-114].

It is theorised that adults visually represent faces in a multidimensional 'face-space'[112-114]. Each dimension in this space corresponds to a way in which faces are perceived to vary (though it is unclear what dimensions are[108]). Every face can be coded based on each of these dimensions, giving it a unique position in face-space. Faces that are perceptually similar (i.e., similar across the dimensions) will be positioned close together in this multidimensional space, while perceptually dissimilar faces will be located far away from each other[113-115]. Although 'face-space' was first devised to explain how individuals code and recognise face *identities* [112-

[117], more recently it was broadened to explain how individuals code and recognise facial *expressions*[108-111].

The most widely accepted model to explain how the visual system codes the position of an incoming facial identity or expression in face-space is the '*norm-based coding'* model[108-112,118-130], which posits that each facial identity or expression is coded according to how much it deviates from a central norm (an average derived from previously encountered facial identities or expressions[108-112]). Under this model, individuals compare incoming facial expressions to stored templates of anger, happiness, sadness, and so on, which are each represented as the average of all previous encounters (i.e., the average angry expression, the average happy expression, the average sad expression, etc.)[108-111]. When an individual perceives that an incoming facial expression is close (in position) to a given template in face-space (i.e., similar across many dimensions), they will categorise the expression accordingly[108-111].

One fruitful way to test whether a norms-based coding system is used to represent a particular sensory input is through *adaptation*[131]. In such a technique, participants' perceptions of stimuli are affected by previous exposure (i.e., *adaptation*) to other stimuli[131]. This technique is successful because exposure to stimuli reduces the responsiveness of neurons that fire for that stimuli, thus altering the neural response to, and thus the perception of, subsequent stimuli[132]. One example of this phenomenon is that, after adapting to constant motion in one direction, individuals perceive stationary stimuli to be moving in the opposite direction[133]. Such alterations to perception are often termed 'aftereffects' in the literature. Importantly, aftereffects can also occur for high-level stimuli such as faces[134-137]. For example, exposure to a distorted face (e.g., eyes raised higher on the forehead than is typical) causes a subsequently viewed typical face to appear slightly distorted in the opposite direction (e.g., eyes appear lower than typical[119]).

In a norm-based coding model, all of the potential values across a dimension in face-space (e.g., height of eyebrows) are thought to be coded based on the relative output of two pools of neurons: one pool responds maximally to high values on the dimension (e.g., eyebrows high up the face) and minimally to low values (e.g., eyebrows far down the face), and the other pool responds with the inverse tuning[138]. According to this model, the "norm" on this dimension (e.g., mean eyebrow height) is perceived when both pools produce the same strength output signal[138]. Therefore, if participants follow a norm-based coding approach, we would predict that adapting to a face at one end of a dimension (e.g., raised eyebrows) affects the reactivity of the pool of neurons tuned to that end (e.g., raised eyebrows) more than the other pool (e.g., lowered eyebrows), thus shifting the norm and creating an aftereffect (e.g., lowered eyebrows)[138]. A stimulus that lies further from the norm (e.g., very raised eyebrows) will produce stronger activation and subsequent suppression of these neurons, thus shifting the norm further along the dimension than a stimulus closer to the norm (e.g., slightly raised eyebrows), creating a larger aftereffect[138].

Here, an important question concerns how we assess adaptation to emotional facial expressions, and thus whether individuals follow a norm-based approach to coding incoming expressions. Typically, researchers will evoke expression aftereffects using a spectrum of facial expressions ranging from a prototypical exemplar (e.g., happiness with raised cheeks and an upturned mouth) to an 'antiexpression' - the physical opposite of the exemplar (e.g., lowered cheeks and downturned mouth)[111,139]. These antiexpressions are created by calculating how far each facial feature in the emotional expression deviates from a neutral expression, and then moving these features in the opposite direction from neutral[111,139]. This distance can then be used to create more intense (e.g., 100% antiexpression) and less intense (e.g., 33% antiexpression) antiexpressions[111,139]. In these paradigms (e.g.,[108]), participants are typically shown the antiexpression for 15 seconds, and then a test 'norm face' (the average of the six basic expressions) for 400ms. Following this, participants are required to label the emotion in the norm face[108].

The idea is that if individuals represent facial expressions in a multidimensional, template-referenced framework, we would expect adaptation to anti-expressions to produce a selective effect on perception[111]; adaptation to each antiexpression should bias perception towards its corresponding 'real' expression, and not to other emotional expressions[111]. That is, we would expect adaptation to an antiexpression of anger to bias perception of a subsequent norm face towards anger, and not happiness, sadness, or fear (and so on). If, however, facial expressions are not represented in this multidimensional, template-based framework, antiexpressions will be perceived as deformations of the face that have no specific meaning relative to the real expression, thus not resulting in such systematic selective biases in perception[111]. That is, if you do not represent facial expressions in a dimensional framework, the opposite of an angry expression (e.g., raised eyebrows) just looks like a deformation of a face and will not bias your perception towards a real angry expression (e.g., furrowed eyebrows). There is growing evidence to suggest that people adopt a norm-based coding model to code and recognise facial expressions for the six basic emotions[108-111]; perceiving antiexpressions of anger, happiness, sadness, fear, disgust and surprise selectively biases our perception (i.e., shifts the template) towards the corresponding expression, and more intense antiexpressions results in larger biases (i.e., larger shifts in the template)[108-111]. Such evidence suggests that individuals code incoming facial expressions based on their relative position to norm expressions (i.e., average exemplars) in a multi-dimensional face-space.

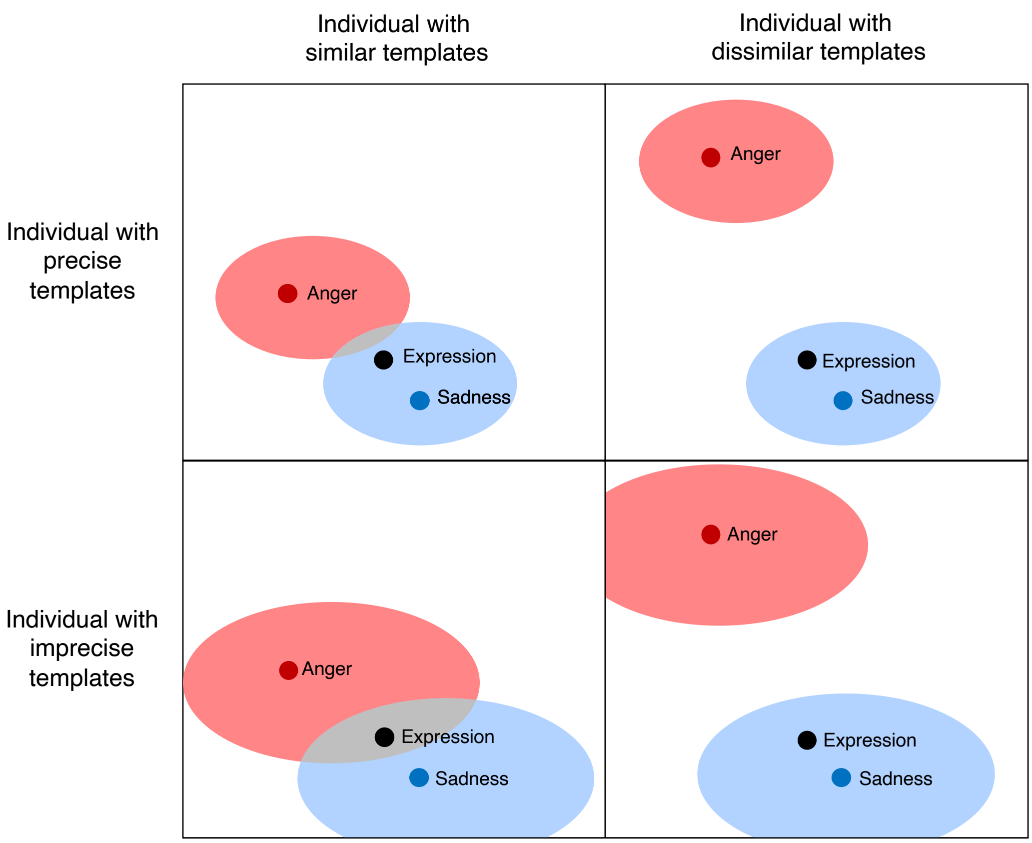
1.3.2. Breakdowns in the conveyance and recognition of emotion

Template-matching models make several predictions as to why individuals may struggle to read the emotions of one's interaction partner. Such models suggest that successful conveyance of emotion depends on the interactants having shared visual representations (i.e., the emotional expression imagined in the mind's eye; templates) and motoric representations of facial expressions (i.e., the emotional expressions produced). That is, in order to recognise the emotion of your interaction partner, they must produce a facial expression which visually matches your 'template' for that emotion. A mismatch between the "producer" and "perceiver" in the appearance of imagined and expressed facial expressions – perhaps with respect to the spatial configuration or the kinematics of facial features – could result in bidirectional difficulties in emotion recognition. However, in addition to visual appearance (e.g., spatial configuration of facial features, or kinematics of facial features, etc.) there may be other features of imagined emotion representations that influence our ability to interpret others' emotions – for instance the precision and/or differentiation of such representations.

Signal detection theory (see [140]) posits that signal and noise distributions that are precise (i.e., narrow) and distinct (i.e., not overlapping) provide high sensitivity to distinguish the signal from the noise. Applying this principle, an individual with a precise representation of anger, that is distinct from the representation for sadness, will be adept at discriminating whether encountered facial expressions are angry or sad. Conversely, someone with imprecise and overlapping visual representations of anger and sadness may struggle to distinguish these expressions (see Figure 1.1, bottom-left). This idea is compatible with the principles of face-space; if the templates for anger and sadness are positioned close together in face-space, it will be difficult to determine which template is closest (i.e., most similar across numerous dimensions) to an incoming facial expression (see Figure 1.1, left). If, however, the templates for anger and sadness are far away from each other in face-space, it will be relatively easy to categorise the incoming facial expression (see Figure 1.1, right). Another important feature is precision; if the templates for anger and sadness are precise (i.e., consistent across instances), it may also be easier to categorise the expression (see Figure 1.1, top), whereas imprecise templates may lead to difficulties due to increased overlap between visual representations (see Figure 1.1, bottom). Notably, however, while there is theoretical justification for a role of the precision and differentiation of visual representations in emotion recognition, research is yet to test this idea.

Figure 1.1.

A schematic depicting the position of angry (red circle) and sad (blue circle) templates and an incoming facial expression (black circle) in face-space



Note. The precision of templates is shown by faded red (angry) and blue (sad) ellipses. This diagram illustrates the potential importance of the precision (high precision: top; low precision:

bottom) and differentiation (poor differentiation: left; good differentiation: right) of visual emotion representations when attempting to match incoming expressions to one's templates.

The ideas discussed above are also compatible with constructionist theories of emotion. As mentioned, it is theorised that we possess multimodal emotion concepts that are made up of sensory (e.g., visual), affective, contextual, and motor information, for example about one's facial movements[13,43,45]. Thus, each emotion concept groups both visual representations of emotions – the visual information about facial expressions that has been stored during instances where these emotions have been labelled or perceived in others – and motoric representations of emotions – proprioceptive information about our own facial movements when these emotions are labelled or perceived in ourselves. As such, our emotion concepts may unite our visual and motoric representations of facial expressions, which are central to template-matching models of emotion recognition, in a multidimensional conceptual space (similar to a face-space format). In addition, our previous affective experiences, and the semantic meanings associated with emotions, are also integrated into our emotion concepts[13]. These features could also be mapped out in a multidimensional conceptual emotion space. Drawing on this idea, if semantic, affective, visual, or motoric representations are imprecise or overlapping, it could be more difficult to assess whether incoming facial expressions belong in one category or another. For example, if your visual representations for anger and sadness are overlapping – perhaps they are both associated with a downturned mouth – it will be difficult to establish whether incoming facial expressions match your template for anger or for sadness. Concurrently, if your visual representation for anger is imprecise – perhaps you have encountered highly variable angry expressions – it will be difficult to determine whether incoming expressions match such a representation. Similarly, if the semantic meaning or core affect (i.e., the levels of arousal and valence) you associate with anger and sadness are imprecise (i.e., variable across instances) and overlapping (i.e., similar to one another), you may find it more difficult to distinguish when you or others are experiencing anger or sadness. Although these are logical possibilities, research is yet to interrogate whether the precision and differentiation of semantic conceptualisations, affective experiences, visual representations, and motoric productions of emotion, contribute to emotion recognition performance.

In sum, together constructionist, template-matching, and signal detection models raise the hypothesis that difficulties interpreting the emotions of others could arise due to less precise or differentiated semantic meanings, experiences (i.e., core affect), visual representations, or productions of emotion. Hence, this work illuminates candidate mechanisms that may underpin the emotion recognition difficulties documented in a range of clinical conditions (see [141-146]) such as autism spectrum disorder (see [146]). These mechanistic pathways are particularly plausible since there is evidence to suggest that autistic individuals may have altered conceptualisations, experiences, visual representations, and productions of emotion[146-150], which could feasibly contribute to emotion recognition difficulties. Before considering this literature at length, it is useful to discuss autism, social cognition, and emotion-processing more generally.

1.4. Autism, social cognition, and emotion-processing

Autism Spectrum Disorder (hereafter 'autism') is a neurodevelopmental condition characterised by socio-communicative difficulties and restricted and repetitive interests[151]. Recent investigations have found that approximately 1.6% of the UK population have a diagnosis of autism[152]. As suggested by its name, autism has a heterogeneous behavioural phenotype, with varying constellations of strengths, differences, and difficulties (e.g.,[153-155]). With respect to the former, autistic individuals frequently show cognitive advantages including enhanced creativity, focus, and memory, along with personal qualities, such as honesty, dedication, and a sense of social justice (e.g.,[156-162]). On the other hand, autistic individuals are thought to have difficulties distributing cognitive resources flexibly[163,164], a tendency towards local rather than global processing[165-168], and challenges understanding others' beliefs and desires (i.e., mental states[106,168,169]). Beyond these challenges, autistic people often experience educational and employment difficulties [170,171], poorer quality of life[172-174], social isolation (see [175]) and suicidality[176]. Since the emergence of the social model of disability (e.g., see [177]), it has been increasingly recognised that some of these difficulties arise due to external factors (e.g., stigma, discrimination, lack of accessibility, etc.), rather than due to factors intrinsic to autism[178-181].

1.4.1. Autism and social cognition

One particular area of difficulty for autistic individuals is thought to be social cognition (see [182]). Social cognition is a broader term representing the cognitive ability to perceive, categorise, and respond to other people's thoughts, intentions and feelings[183]. Social cognition enables the acquisition of knowledge and social skills, promotes the success and fluidity of social interactions, and facilitates the formation and maintenance of social relationships (see [184-186]). Hence, social cognitive abilities play a major role in everyday life and in psychosocial outcomes. Social cognition can be divided into several sub-abilities including social orientation, theory of mind, emotion recognition, and emotion expression (amongst others[187]). Notably, differences have been documented between autistic and non-autistic individuals across all of these sub-abilities: autistic individuals show reduced social orienting (see [188]), difficulties inferring the mental state (see [189,190]) and emotions of others (see [146,191]), and differences in the production of emotional facial expressions (see [146,150]).

1.4.2. Autism and emotion-processing

In addition to having emotion-related difficulties in the interpersonal domain (e.g., difficulties recognising emotions of *others),* autistic individuals are also thought to have intrapersonal emotional difficulties. For example, there is evidence to suggest that autistic individuals have difficulties acquiring, developing, and differentiating emotion concepts (see [148,192]), and co-occurring challenges identifying, understanding (see [149]), differentiating[148] and regulating[193] their own emotions. At present, it is not clear whether these difficulties are related, and/or whether emotion difficulties in the intrapersonal domain precipitate difficulties in the interpersonal one (or vice versa). That is, it is unclear whether difficulties understanding, identifying or differentiating emotion concepts or emotional experiences underpin the emotion recognition and production differences seen in autism.

In sum, a growing body of evidence suggests that autistic individuals have broad social and emotional difficulties. However, when considering this evidence, it is imperative to note the role of alexithymia – a subclinical condition characterised by challenges identifying and describing one's own emotions[194].

1.4.3. The alexithymia hypothesis

The term "alexithymia" was first coined in 1973 to describe a group of patients with psychosomatic illnesses who showed additional difficulties interpreting their own emotions[195]. Today, alexithymia is widely regarded as a transdiagnostic risk factor for a numerous mental health conditions including psychosis, depression, anxiety, and eating disorders (e.g., see [196-198]). Besides these conditions, alexithymia is also highly prevalent in the autistic population, with around half of autistic people experiencing co-occurring alexithymia, in comparison to just 5% of neurotypicals[199]. This elevated prevalence, alongside evidence that (neurotypical) individuals high in alexithymia show reduced emotional reactivity[200,201], empathy[202-205], and emotion recognition performance (see [206]), led to the proposition of "the alexithymia hypothesis"[207]. This hypothesis proposes that autistic individuals' difficulties with emotion-processing are caused by co-occurring alexithymia, and not autism[207]. There is growing support for this hypothesis (e.g.,[208-214]), though notably the majority of this research has focused on the domain of emotion recognition. Thus, currently it is unclear whether differences exist between autistic and non-autistic individuals in the conceptualisation, experience, visualisation, and production of emotion, after controlling for alexithymia.

For the remainder of Chapter 1, I synthesise the previous findings regarding these emotion-related factors in autism and, where possible, discuss the evidence from studies controlling for alexithymia.

1.4.4. Recognising emotional signals in autism

As discussed, the ability to infer the emotions of one's interaction partner is important for social interaction (see [102]). Since autism is characterised by difficulties with such interactions, emotion recognition has been suspected as a difficulty for autistic individuals for over three decades[215]. However, the existing literature is rife with mixed findings (see [146, 191, 216-218]): some studies find global differences in emotion recognition between autistic and non-autistic people, while others show no differences, or emotion, task, or stimuli-specific difficulties (see [146, 191, 216-218]).

A growing literature suggests autistic individuals may have emotion-specific difficulties with facial expression recognition (e.g., see [191]). For example, numerous empirical studies (e.g., [147,219-223]) and meta-analytic evidence (e.g., [191]) demonstrate that autistic individuals may have selective emotion recognition difficulties for expressions of anger, but not happiness or sadness. At present, it is unclear why autistic individuals have specific difficulties recognising anger, however, there are a number of potential explanations. It could be, for example, that differences in facial information sampling play a role. Since autistic individuals typically spend less time attending to the eyes, and more time attending to the mouth, (relative to non-autistic individuals [224-226]), they may struggle to recognise anger, as the upper half of the face conveys the majority of the expressive information (e.g., [227,228]). Alternatively, since autistic individuals display slowed processing of emotional facial expressions[229-238], it could be that these individuals have particular difficulties recognising angry facial expressions due to them being inherently fast-moving[239]. Another possibility is that autistic individuals visualise and/or produce different emotional expressions of anger themselves, and thus the non-autistic expressions presented to them do not match their expectation, resulting in difficulties interpreting the expression (see emotion recognition theories above). Finally, it is possible that autistic individuals themselves have less precise and/or differentiated experiences or visual representations of anger, which underpin their emotion recognition difficulties. Although these are logical possibilities, research is yet to test these ideas.

The existing literature also points towards potential task and stimuli-specific difficulties in emotion recognition. For example, it appears that autistic individuals may have particular difficulties recognising low intensity expressions (e.g., [222,240,241]), and not "full blown" prototypical expressions (e.g., [242-244]). Alternatively, autistic individuals may struggle to recognise emotion in certain types of stimuli, for example in point-light (series of dots that convey biological motion; see [245]) but not full displays (e.g., photos or video recordings[221]).

In addition to these task-related factors, participant characteristics (e.g., age, extent of alexithymia) may also influence the magnitude of differences between the autistic and non-autistic participants. For example, Lozier and colleagues[191] found that age significantly moderated the effect of group on emotion recognition performance. Specifically, these authors found that although both child and adult autistic participants displayed emotion recognition difficulties (relative to their non-autistic counterparts), these differences were greater in the adult group. Other empirical work has found that whilst emotion recognition improves throughout life for non-autistic individuals, it does not for autistic individuals[246], further suggesting age plays a moderating role.

Another participant characteristic that may contribute to elevated emotion recognition difficulties in the autistic population is alexithymia. As mentioned previously, it is theorised that autistic individuals' difficulties with emotion recognition are not caused by autism *per se*, but rather alexithymia (i.e., the alexithymia hypothesis[199,207,247]). There is growing empirical support for this hypothesis. Cook and Brewer et al[209], for example, showed that when autistic and non-autistic individuals were matched on levels of alexithymia, they had a comparable ability to recognise emotion from static face images. Supporting the alexithymia hypothesis, this study also found that alexithymic traits, but not autistic traits, predicted poorer emotion recognition performance. Similarly, Milosavljevic et al[213] found that autistic individuals high, relative to low, in alexithymia had greater difficulties recognising emotion, again from static snapshots of faces.

Notably, to date, the majority of studies assessing the relative contributions of autistic and alexithymic traits to facial emotion recognition have employed static face stimuli, thus overlooking the inherent dynamicity of facial expressions[248,249]. Prior to this project, only one study had investigated whether autistic and alexithymic traits contributed to emotion recognition for dynamic stimuli[212]. This study found support for the alexithymia hypothesis: alexithymia, and not autism, was associated with poorer facial emotion recognition for dynamic displays[212]. While these results are informative, there were two key limitations of this study. Firstly, the authors only included female participants. Since autistic males and females often possess different behavioural phenotypes[250-253], it may be that these findings are not representative of autistic males. Secondly, the authors did not include a non-autistic comparison group. As such, they were unable to assess whether there were differences between autistic and non-autistic individuals in emotion recognition from dynamic stimuli, after controlling for alexithymia. Thus, further research, which employs a non-autistic comparison group and involves males, is necessary to determine whether autistic versus non-autistic group differences remain after accounting for the confounding influence of alexithymia.

In sum, although existing literature suggests that autistic people may have difficulties interpreting the emotions of other people (see [146,191,216-218]), most of this work has not assessed the contribution of alexithymia, and therefore it is unclear whether these difficulties remain after controlling for this factor. While a handful of studies *have* tested whether autistic or alexithymic traits contribute to emotion recognition, these studies have solely relied on static snapshots of faces[209,123], omitted a non-autistic comparison group[212], and/or exclusively included female participants[212]. Therefore, future research should aim to test whether there are differences in dynamic emotion recognition for both male and female autistic and non-autistic individuals matched on alexithymia. Concurrently, although there is evidence to suggest that autistic individual may have greater difficulties recognising some emotions (e.g., anger [147,191, 219-223]) than others, it is currently unclear why. Therefore, future studies should aim to unpick the mechanisms underpinning these selective emotion recognition difficulties, assessing whether such challenges stem from differences in other emotion-related psychological processes (e.g., the conceptualisation, experience, visual representation, and production of emotion).

Mechanistic differences in autistic and non-autistic emotion recognition

Although the vast majority of research has aimed to determine whether there are *differences* in emotion recognition between autistic and non-autistic individuals, a handful of studies have aimed to elucidate the *mechanisms* involved in emotion recognition for these groups. This research is imperative for making progress: identifying the mechanisms involved could illuminate why autistic individuals have greater difficulties on some tasks than others, thus explaining the inconsistent findings in the literature (see [146]). Moreover, such research could help us to design tailored support systems, focusing on these mechanisms, to help both autistic and non-autistic individuals to recognise the emotions of others', with potential benefits for psychosocial adjustment[254] and psychological health and wellbeing[255].

There is preliminary evidence to suggest that different mechanisms may be involved in autistic and non-autistic emotion recognition. While neurotypical adults are thought to employ a template-matching strategy to recognise the emotions of others[108-111], it is theorised that autistic adults may follow a rule-based strategy[256,257]. That is, rather than automatically comparing incoming facial expressions to stored templates, autistic individuals may evaluate whether the expressions match a set of characteristics they have learnt to be associated with different emotions (e.g., happiness: "smiling", anger: "furrowed brow"[256,257]).

To test this idea, previous studies have presented autistic and non-autistic observers with emotional expressions that vary in intensity (e.g., 100, 150, 200, 250 and 300%), and asked them to select which examples appear realistic[256,257]. The logic was that, if individuals employ template-matching, naturally exaggerated expressions (e.g., 100%, intensity) would match the template and thus appear realistic to participants, while unnaturally exaggerated ones (e.g., 250%, 300% intensity) would be unrealistic representations of the expression. Conversely, if individuals adopt a rule-based strategy, they would be more tolerant of unnaturally exaggerated expressions (i.e., the highly exaggerated expressions appear relatively more realistic), because the rules such as "upturned mouth" and "furrowed brow" are still true[256,257]. Across both studies, the autistic adults selected a higher proportion of exaggerated faces as realistic (relative to their non-autistic peers), suggesting they had a higher tolerance for exaggeration, and thus raising the possibility of a more rule-based strategy[256,257].

Although these findings could be indicative of a rule-based strategy, there are alternative explanations for these results. For example, it could be that the autistic participants are comparing incoming expressions to more exaggerated templates (relative to non-autistic participants), and thus the highly exaggerated expressions appear more realistic to them (as they are a closer match to the template). That is, the autistic participants may have more caricatured visual emotion representations, leading to a higher tolerance for exaggeration of facial expressions. This explanation is plausible since recent work has found that autistic people require emotional expressions to be higher in intensity (relative to non-autistic individuals) in order for them to be correctly identified[222,240]. Hence, the autistic participants may have more exaggerated visual representations, thus leading to higher tolerance for exaggeration[222,240], and lower emotion recognition accuracy when expressions are less intense[222,240,241] (as they do not match their templates).

Nevertheless, there are other findings which indirectly support the idea that autistic individuals may be employing alternative rule-based strategies. Firstly, if autistic individuals employ cognitive or verbally mediated strategies, emotion recognition performance should be more strongly associated with cognitive or verbal ability for autistic, relative to non-autistic, individuals. Supporting this idea, there is evidence to suggest that mental age[215] and verbal ability[258] predict emotion recognition performance for autistic children, but not non-autistic children. Second, if it is true that autistic individuals employ more effortful cognitive mechanisms, we would expect longer emotion recognition response latencies, which have been documented on numerous occasions (e.g.,[229-238]; though notably there are other explanations for this finding). Thus, the evidence tentatively points towards (some) differences in the mechanisms involved in emotion recognition for autistic and non-autistic people.

The idea that autistic individuals may naturally be less guided by their visual emotion representations aligns with Bayesian accounts of autism. According to these accounts, autistic people are less affected by their prior experiences (i.e., previously acquired information; priors) than neurotypicals, instead placing greater weight on incoming sensory information (e.g., [259-261]). Thus, in the domain of recognition, an autistic person would place less emphasis on their stored templates, which they have acquired through past experiences, and instead focus on the intrinsic properties of the incoming facial expressions. In addition, Bayesian theories may predict autistic individuals to place less emphasis on other conceptual emotion information, which is also said to be acquired through experience (see [13]) – the core affect, semantic meanings, and motor responses (e.g., own facial expressions) associated with an emotion. However, these ideas have not yet been tested formally.

In sum, there is theoretical justification and preliminary evidence for mechanistic differences in autistic and non-autistic emotion recognition. However, further work is necessary to identify the traits, abilities and processes involved for both groups, and to determine whether such factors underpin the emotion recognition difficulties often found for autistic individuals.

1.4.5. Producing emotional signals in autism

There are a number of factors to consider when examining the production of emotional facial expressions in autism, for example the frequency, duration, intensity, quality, accuracy, and general appearance of expressions. With respect to the former, numerous empirical studies, and meta-analytic evidence, suggest that autistic children typically produce facial expressions less often and for shorter durations than their non-autistic counterparts during naturalistic social interactions[150, 262-264]. To date, there are mixed findings with respect to the intensity of produced facial expressions. In some studies, autistic expressions are subjectively rated as more intense (e.g., [265-267]), while in others the opposite is true[263,268-270]. A small number of studies have employed more objective measures, such as facial electromyography (fEMG), to assess differences in facial expressions. The evidence from these studies contradicts that from subjective ratings, finding no differences between autistic and non-autistic participants in expressivity while viewing emotional stimuli[271-274], when voluntarily mimicking emotional expressions[274,275], and during automatic imitation[276]. Notably, it could be that these null effects arise due to fEMG not being sensitive to differences in the activation of all facial muscles: traditionally fEMG is limited to studying two muscle groups; (1) the corrugator supercilii, which is responsible for frowning, and (2) the zygomaticus major, which is responsible for smiling[277]. A more promising tool for analysing expressive differences is facial motion capture as it records movements of the skin surface across the entire face with high temporal resolution, such that subtle changes in expression can be recorded every few milliseconds[277]. Thus, future studies should aim to employ this technique to compare the facial expressions of autistic and non-autistic individuals.

Concurrently, the extant literature points towards differences between autistic and non-autistic individuals in the quality, accuracy, and general appearance of facial expressions (see [146,150]). In numerous empirical studies, expressions produced by autistic individuals (relative to non-autistic individuals) are perceived as lower in *quality* and *atypical in appearance*, being rated as odd, awkward or mechanical by non-autistic observers[263,265,266,278]. Concurrently, research has shown that autistic children mimic facial expressions less accurately than their non-autistic peers (i.e., with lower congruency to the displayed expression[270,275]). In sum, the evidence from empirical and meta-analytic studies suggests that autistic individuals produce facial expressions less often and for shorter durations, and that such expressions are less accurate, lower in quality, and atypical appearance, according to non-autistic observers (see [146,150]).

Despite growing evidence for differences in the facial expressions produced by autistic and non-autistic individuals, studies have not yet characterised what specifically is different about them[146]. There are a number of ways to quantify facial expressions. Firstly, one can look at the configuration of facial features and assess whether there are spatial differences between groups (e.g., does one group furrow their brow further when expressing anger)[146]. Secondly, one can look at *how* individuals reach these configurations by asking whether there are kinematic differences (e.g., does one group furrow their brow more quickly or in a more jerky fashion)[146], or differences in the temporal profile of expressions (e.g., one group furrows their brow and then purses their lips, while the other moves these regions simultaneously). However, despite notions of differences between groups, studies are yet to fully compare the spatiotemporal and kinematic properties of autistic and non-autistic facial expressions. Nevertheless, this is an important avenue for future research because the findings of such studies could have great utility, allowing caregivers and clinicians to be trained to interpret autistic facial expressions, thus facilitating more successful and fluid social interactions[146].

When conducting such studies, future research should aim to address the limitations of previous research investigating expressive differences. Thus far, previous studies have not controlled for facial morphology, which is known to differ between autistic and non-autistic individuals[279-282]. Such differences in facial morphology could underpin subjective ratings of autistic expressions as odd, mechanical or awkward[263,265,266,278]. Thus, future studies comparing the facial expressions produced between these groups should attempt to control for morphological differences. Such studies will allow us to determine whether differences in the appearance of facial expressions are truly underpinned by differences in facial movements or by facial morphology. Second, as mentioned previously, the vast majority of previous studies have not controlled for alexithymia. However, any study comparing the facial expressions produced by autistic and non-autistic individuals should model the contribution of alexithymia to avoid erroneously attributing differences to autism (see the alexithymia hypothesis[207]). Indeed, this is particularly pertinent since recent evidence suggests that alexithymic, but not autistic traits are related to reduced presentation duration for spontaneous facial expressions[214]. Further research is necessary to assess whether alexithymia underpins the differences in the facial expressions produced by autistic and non-autistic individuals with respect to intensity, overlap, and general appearance.

1.4.6. Bidirectional difficulties in emotion recognition; Differing visual representations?

Since template-matching models assert that successful conveyance of emotion relies on common visual and motoric representations of facial expressions between interactants (e.g., [108-111]), it is reasonable to assume that a mismatch in the production of facial expressions could lead to bidirectional emotion recognition difficulties for autistic and non-autistic individuals. Notably, however, the vast majority of research has examined how well *autistic* individuals can recognise *non-autistic* facial expressions, and not the other way round. Nevertheless, although the evidence is mixed, the very few studies that have assessed how well non-autistic individuals can recognise autistic expressions have generally reported difficulties (e.g., [147,278,283] though see [265,267]).

One particular study that both contributes to this literature, and sheds light on the mechanisms underpinning expressive differences is by Brewer and colleagues[147]. In this study, the authors took video recordings of autistic and neurotypical participants posing the six basic emotions across three conditions: (1) the standard condition, in which participants posed each emotion to the best of their ability; (2) the "communicate" condition, wherein participants were required to pose such that an experimenter could guess the emotion that was being expressed; and (3) the mirror condition, in which participants were able to view their own expression during production[147]. These latter conditions were incorporated to assess whether any groups differences stem from autistic individuals not recognising the communicative nature of facial expressions, or due to reduced awareness of their facial movements (i.e., proprioceptive differences[147]). Next, Brewer and colleagues[147] asked autistic and neurotypical participants to match static snapshots of the recorded facial expressions with one of six prompted emotion labels (anger, happiness, sadness, surprise, fear and disgust).

Interestingly, across all conditions, both the autistic and neurotypical participants had greater difficulties recognising the expressions produced by autistic posers (relative to neurotypical posers[147]). In addition, both groups produced more recognizable expressions when the researchers emphasised the communicative function of expressions, and when participants had access to visual feedback[147]. Notably, this improvement across conditions was comparable between groups[147]. Together, this evidence suggests it is not the case that autistic people are less aware of the informative nature of facial expressions (which would have caused larger improvement in the communicate condition for the autistic than neurotypical group), nor less able to leverage proprioceptive feedback than their neurotypical counterparts (which would have caused larger improvements in the mirror condition)[147]. Rather, after receiving visual feedback and explicit instruction to convey emotions, autistic individuals still produce different emotional expressions, suggesting that these individuals may have different visual emotion representations to their non-autistic peers[147]. This idea of atypical representations in autism, alongside the finding that both the autistic and neurotypical participants had greater difficulties recognising autistic expressions, illuminates two theoretical possibilities. Firstly, it could be that autistic individuals produce atypical facial expressions which are idiosyncratic, rather than shared (amongst other autistic individuals), thus leading to difficulties recognising autistic expressions for *both* autistic and neurotypical people[147]. Essentially, under this explanation, neither autistic nor neurotypical individuals are able to recognise autistic facial expressions, as they are unique to the specific autistic individual and thus do not match the perceiver's visual representations (irrespective of whether the perceived is autistic or neurotypical). A second possibility is that autistic individuals produce atypical facial expressions, which systematically differ from those produced by neurotypicals, but that this group place less weight on their visual and/or motoric representations when recognising others' emotions. Under this explanation, the neurotypical individuals struggle to recognise autistic expressions as they differ from their own visual representations, whereas the autistic individuals struggle to recognise them because they are not *using* their visual or motoric representations (or using them to a lesser extent), which comprise a good match to incoming autistic expressions, to recognise the emotions of other people. This latter explanation is compatible with previous arguments that autistic individuals do not compare incoming expressions to their visual representations (i.e., templates) and instead follow a rule-based strategy[256,257], and/or focus on the sensory properties of the stimuli (e.g., [259-261]). This explanation can also account for why the autistic participants had a better ability to recognise the expressions produced by neurotypical than autistic posers. Under this explanation, the autistic individuals may be better able to recognise neurotypical expressions because they more clearly show the features they have learnt to be associated with distinct emotions (as such learning may primarily be based on neurotypical expressions which they encounter relatively more frequently than autistic expressions). Further work is necessary to explore these theoretical possibilities.

In sum, irrespective of the degree to which autistic individuals are guided by their representations, the results from Brewer and colleagues[147] suggest that autistic individuals may have *different* visual emotion representations to their non-autistic peers. This idea is also supported by the literature discussed previously: autistic individuals rate highly exaggerated expressions as relatively more realistic (compared to non-autistic individuals[256,257]), and require emotional expressions to be higher in intensity (relative to non-autistic individuals) in order for them to be correctly identified[222,240]. Together, this evidence suggests that autistic people may have caricatured visual representations of emotion.

While informative, the results from previous studies (e.g., [147,222,240,256,257]) have led researchers to *indirectly* infer that visual emotion representations may be atypical in autism, without *direct* investigation. That is, studies have shown differences in the production of emotional facial expressions[147], the appraisal of highly exaggerated stimuli[256,257], and in identification thresholds[222,240], which point to differences in visual representations, however, the appearance of such representations has not been interrogated. Future studies could benefit from employing psychophysical techniques, such as the method of adjustment (see [284]), to allow autistic and non-autistic individuals to manipulate features of emotional expressions such that they match their visual emotion representations. Following this, features of these representations can be compared statistically between groups. In addition, previous studies suggesting atypical visual representations in autism (e.g., [147,222,240,256,257]) have specifically focused on static emotional expressions, and pointed to differences in the spatial domain (i.e., spatial exaggeration of facial features). As such, it is unclear whether autistic and non-autistic individuals possess different visual emotion representations for dynamic expressions, and whether these differences specifically pertain to the kinematics (e.g., speed, acceleration, jerk, etc.), the temporal order (i.e., the way in which the expressions unfold), or spatial exaggeration of expressions (or other features). Further research is necessary to confirm this.

Another important avenue for future research is to assess whether differences in visual emotion representations contribute to emotion recognition accuracy for autistic and non-autistic individuals. In particular, since the aforementioned theories suggest that the precision and differentiation of visual representations may play a role, future studies should aim to assess whether there are differences between autistic and non-autistic individuals in these factors, and examine whether any differences therein contribute to emotion recognition differences. It could be, for example, that autistic individuals' selective difficulties recognising anger (e.g., [147,191,219-223]) stem from imprecise or overlapping visual representations of anger.

Although this is yet to be tested in the domain of facial emotion recognition, links have been found between these factors for facial identity. For example, one study showed that participants who had built up more precise visual representations of facial identities from multiple views, relative to a single view, were better able to subsequently recognise those faces from a novel perspective[285]. Thus, illuminating a role of the precision of visual representations in the recognition of facial identities. Concurrently, it is well known that it is more difficult to differentiate and recognise identities that are overlapping in appearance[286]. As such, the face identity literature raises the hypothesis that individuals that struggle with emotion recognition may have imprecise and/or poorly differentiated visual emotion representations. Hence, future studies should examine whether differences exist between autistic and non-autistic individuals on these factors, and determine whether such differences underpin emotion recognition challenges for autistic individuals.

1.4.7. The conceptualisation and experience of emotion in autism

A limited body of work has assessed the understanding, conceptualisation, and experience of emotion in autism (see [149,192]). Although this body of evidence suggests that autistic individuals may have difficulties identifying and describing their emotions (see [149]), and challenges acquiring, developing, and differentiating emotion concepts (see [148,192]), such work has heavily relied on self-report measures (89.4% in of studies in Huggins et al.[149]). This may be problematic for a number of reasons. Firstly, there are often weak associations between self-reported and objectively measured emotional abilities[287,288]. Secondly, self-report measures of emotional self-awareness may be particularly problematic for use with autistic individuals as such measures rely on meta-cognition, which autistic people may struggle with[289-291]. Hence, autistic individuals may be less accurate in their estimation of their emotional abilities, thus threatening the validity of self-report measures. This is particularly plausible since previous research has found that being high in autistic traits was associated with a greater discrepancy between self-reported and behaviourally measured emotional self-awareness[292].

Although a handful of objective methods have been developed to assess the experience of emotion (e.g.,[148]), finding evidence that autistic individuals have less differentiated experiences and semantic concepts of emotion[148], such studies have failed to account for alexithymia. Erbas and colleagues[148], asked participants to rate the extent to which they experienced 20 emotion labels in response to a series of standardised emotional images[148]. Using this task, an index of emotion differentiation was calculated for each participant by computing the intra-class correlation coefficients (ICC), assessing consistency in intensity ratings between emotion labels, across images. The logic here was that if participants gave consistently similar ratings for two emotions (e.g., anger and sad ratings) across the images, they were not differentiating between these two states[148]. Thus, high ICCs indicated lower levels of emotion differentiation (see [293]). In a second task, participants were required to sort the 20 emotion terms into groups that they thought belonged together. The individuals that divided the emotion terms into a higher number of groups were said to make more fine-grained distinctions between semantic emotion concepts[148]. Erbas and colleagues found that, compared to the non-autistic participants, the autistic participants had higher ICCs and divided emotion terms into fewer groups, indicating that they had less differentiated semantic concepts and experiences of emotion[148]. As mentioned, an important limitation of this study is that it did not control for, or assess the contribution of, alexithymia. Therefore, it is possible that the authors erroneously attributed the difficulties differentiating semantic concepts and experiences of emotion to autism, when these difficulties actually stem from underlying alexithymia (as suggested by the alexithymia hypothesis[207]). As such, future research should assess whether autistic individuals have less differentiated experiences and semantic concepts of emotion, after accounting for this important confound.

Relatedly, preliminary research indicates that alexithymia, and not autism, is linked to the precision of emotional experiences, however, this has not yet been established in clinical samples[292]. To assess emotional precision, Huggins and colleagues[292] asked participants to select which of two images evoked a more intense emotional response. There were four emotional 'test' conditions: an 'easy' and a 'hard' condition wherein participants had to judge which of the two images they found more 'pleasing', and an 'easy' and a 'hard' condition wherein participants judged which of the two were more 'upsetting'. The authors manipulated task difficulty by selecting images which covered either a narrow range (hard condition) or a broad range (easy condition) of valence intensity ratings. In each condition, 11 different images were employed, and thus there were 55 unique image combinations. Emotional precision was calculated for each condition based on the logical consistency of decision-making: if a participant selected image one over image two, and image two over image three, but then selected image three over image one, this latter decision would be inconsistent with their previous judgements, and would result in a reduction in their precision score (see Chapter 4 for more details). This study found that the precision of emotional experiences was (negatively) correlated with alexithymic but not autistic traits in the general population[292], suggesting that those high in alexithymia have less precise emotional experiences across instances. Although these findings are informative, one should be cautious about assuming these results, which pertain to the contribution of autistic and alexithymic traits in a general population sample, extend to autism (i.e., to individuals diagnosed as autistic; see [294] for a full explanation). Hence, further work is necessary to establish whether there are differences between autistic and non-autistic individuals in emotional precision, after controlling for alexithymia.

The research field currently lacks psychological mechanistic models that can help us understand challenges with emotion recognition in the context of autism. As discussed, the existing evidence points towards difficulties for autistic individuals in differentiating semantic concepts and experiences of emotion. An important question is, therefore, what are the consequences of these difficulties for emotion recognition? As mentioned previously, constructionist and signal detection theories suggest that those with less differentiated semantic concepts or emotional experiences would have greater emotion recognition difficulties, as they would have a less precise and differentiated framework for labelling other people's emotions[13,50]. In support of this idea, previous evidence suggests that (non-autistic) individuals who are poorer at differentiating their own emotional experiences are also less able to differentiate others' emotions[295]. As such, it is plausible that difficulties differentiating semantic concepts and experiences of emotion underpin the emotion recognition challenges of autistic individuals (or vice versa). However, further research is necessary to test whether this is the case.

1.5. General limitations of extant autism research

There are a number of general limitations of extant autism research that should be addressed in future studies. Firstly, despite autism being a lifelong condition, the vast majority of autism research is conducted with children, with just 3 to 3.5% of research involving autistic adults[296,297]. As such, there is a paucity of knowledge regarding the abilities and experiences of, and issues affecting, autistic adults. This gap has led to multiple international calls for increased representation of this group in future research[296,298,299], and the advent of *Autism in Adulthood*, a journal dedicated to closing this gap. Hence, future studies specifically focusing on autistic adults are necessary to help increase our understanding of the experiences, behaviours, and abilities of this group.

Another general limitation of autism research is that the majority of studies enrol small samples of autistic females, or exclude this group altogether. Historically, autism has been perceived as a predominantly male condition, with approximately 4 autistic males to every 1 autistic female[300]. However, more recent studies point towards smaller male to female sex ratios, with some samples even documenting equal prevalence across genders (see [301,302]). Notably, when existing diagnostic tools (e.g., the Autism Diagnostic Observation Schedule[303]) are used to verify autism status, the male to female sex ratio is higher than when individuals are given the opportunity to self-diagnose (see [302]). This is likely because females face greater barriers to obtaining autism diagnoses: since gold-standard instruments (e.g., Autism Diagnostic Observation Schedule[303]) are predominantly based on the behavioural phenotype of autistic males[303,304], which differs from that of females (e.g., [250-253]), such assessments may poorly identify autistic females[305-308]. These assessments may also struggle to diagnose autistic females as this group camouflage their autistic traits more in both social and clinical settings than their male peers[309-311]. Overall, this evidence suggests that autistic females are under-diagnosed, and thus ratios derived from self-identification may be more representative of the true prevalence of autism. In such studies, the male to female ratio is around 2:1 (see [302]). The next question, therefore, is to what extent are autistic men and women being included in research? Across studies published in autism journals between 2010 and 2012, 82.22% of the participants were male[312], and 17.30% of studies excluded females entirely[312]. Similarly, a recent review identified that while 434 studies assessing neural functioning in autism employed male-only samples, just four employed female-only samples[313]. These findings demonstrate that autistic females are often underrepresented and systematically excluded from autism research. There are numerous consequences of this. Employing consistently small samples of autistic females compromises our ability to fully understand the experiences, behaviours, and issues affecting autistic females[302], and further perpetuates the idea that autism is a male condition, thus creating a cycle in which future research is constrained to exploring specific male phenotypes[302]. As such, further research is necessary to characterise the behavioural presentation of autistic females, and increase the extent to which they are represented in research (e.g., [312,314,315]).

Another general limitation of autism research is that the majority of studies do not employ participatory methods[316-318]. There are numerous advantages of adopting participatory-style approaches: community input can strengthen the quality of research, ensure the accessibility and efficacy of tasks and materials, and ultimately facilitate translation of findings into practice[318-322]. Such methods also help to foster positive relationships and trust and between researchers, autistic people, and their allies[323]. Although participatory research is rare[316-318], increasingly, studies are emerging which have meaningfully involved the autism community, leading to broad benefits for research (e.g., [316,318,324-330]). Future studies should also aim to adopt such approaches, thus leading to enhanced quality, accessibility and impact of the research.

In sum, thus far, autistic adults and autistic women have been underrepresented in autism research – leading to poorer understanding of the experiences, behaviours, and abilities of these groups – and participatory methods have rarely been adopted – perpetuating an "about us without us" (p. 1) discourse [331]. Therefore, in the current project, I specifically focus on the abilities of autistic adults, ensuring that autistic women are represented in our samples, and adopt participatory approaches throughout.

1.6. Summary and rationale

In sum, preliminary work points to differences in the conceptualisation, experience, visualisation, production, and recognition of emotion between autistic and non-autistic individuals. However, to date, the majority of previous work has not controlled for alexithymia, and thus it is unclear whether such differences arise due to autism or due to co-occurring alexithymia. As such, one of the primary aims of my doctoral work was to determine whether differences exist between autistic and non-autistic individuals in these emotional abilities after controlling for alexithymia. Hence, in the following chapters, I assess the relative contributions of autistic and alexithymic traits to the recognition (Chapter 2), visual representation (Chapters 3, 4 and 5), experience (Chapter 6), conceptualisation (Chapter 6), and production (Chapter 7) of emotion.

Moreover, constructionist, template-matching, and signal detection theories raise the hypothesis that emotion recognition difficulties could stem from a number of factors: specifically, autistic individuals may possess less precise or less differentiated experiences, visual representations, semantic meanings, or productions of emotion. However, thus far, very few studies have tested these predictions and/or assessed the contribution of these emotion-related factors (i.e., the precision and differentiation of experiences, visual representations, semantic meanings and productions of emotion) to emotion recognition. If these factors do contribute, it is plausible that the putative differences between autistic and non-autistic people in these emotional abilities could underpin the emotion recognition challenges often documented in the autistic population. Therefore, in this project, another primary aim was to empirically assess whether the way in which autistic and non-autistic individuals experience (Chapters 3 and 6), visualise (Chapters 2 and 5), conceptualise (Chapter 6) and produce (Chapter 7) emotion contributes to their ability to recognise others' emotional expressions. In doing so, I aimed to build models elucidating the similarities and differences in the mechanisms involved in both autistic and non-autistic emotion recognition (see Chapter 8).

Chapter 2: Differences between autistic and non-autistic adults in the recognition of anger from facial motion remain after controlling for alexithymia

As discussed in the Introduction, the extant literature suggests that autistic individuals may have difficulties recognising the emotions of other people (see [146, 191, 216-218]). However, to date, the majority of this work has not assessed the contribution of alexithymia, and therefore it is unclear whether these difficulties remain after controlling for this factor. Although a handful of studies *have* examined whether autistic or alexithymic traits contribute to emotion recognition, thus supporting the alexithymia hypothesis[207] (i.e., alexithymia, not autism contributes), these studies have solely relied on static snapshots of faces[209,123], omitted a non-autistic comparison group[212], and/or exclusively included female participants[212]. Therefore, prior to this project, it was unclear whether autistic versus non-autistic group differences in emotion recognition for dynamic stimuli, for both males and females, remain after controlling for alexithymia. To address these limitations, in the following chapter, I assessed whether there were differences in the ability to recognise emotion from dynamic stimuli for both male and female autistic and non-autistic individuals matched on alexithymia.

Publication 1:

Differences between autistic and non-autistic adults in the recognition of anger from facial motion remain after controlling for alexithymia.

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(Published in the *Journal of Autism and Developmental Disorders*)

Reference: Keating CT, Fraser DS, Sowden S, Cook JL. Differences between autistic and non-autistic adults in the recognition of anger from facial motion remain after controlling for alexithymia. Journal of autism and developmental disorders. 2022 Apr;52(4):1855-71. https://doi.org/10.1007/s10803-021-05083-9

Abstract

To date, studies have not established whether autistic and non-autistic individuals differ in emotion recognition from facial motion cues when matched in terms of alexithymia. Here, autistic and non-autistic adults (N=60) matched on age, gender, non-verbal reasoning ability and alexithymia, completed an emotion recognition task, which employed dynamic point light displays of emotional facial expressions manipulated in terms of speed and spatial exaggeration. Autistic participants exhibited significantly lower accuracy for angry, but not happy or sad, facial motion with unmanipulated speed and spatial exaggeration. Autistic, and not alexithymic, traits were predictive of accuracy for angry facial motion with unmanipulated speed and spatial exaggeration. Alexithymic traits, in contrast, were predictive of the magnitude of *both* correct and incorrect emotion ratings.

2.1. Introduction

Autism spectrum disorder (ASD) is a neurodevelopmental disorder, characterised by difficulties in social communication, and restricted and repetitive interests[151]. Since the ability to infer emotion from facial expressions is important for social interaction, emotion recognition has long been suspected as a difficulty in autism[215]. However, whilst many studies suggest a disparity in the facial emotion recognition ability of autistic and non-autistic individuals (e.g., [206,332-334]), there have been inconsistent findings, ranging from no differences between these individuals to large disparities (see [146,216,217] for reviews). Consequently, the question of whether autistic individuals exhibit atypical facial emotion recognition has been debated for over 30 years.

The most recent contributions to this debate claim that it is not autism *per se* that is linked to emotion recognition atypicalities but rather alexithymia[199,207,247,335]. Alexithymia is a subclinical condition, characterised by difficulties identifying and expressing emotions[194], which is often comorbid with ASD (in the neurotypical population the prevalence of alexithymia is 4.89%, and in autistic populations the prevalence of alexithymia is 49.93%[199]. Cook, Brewer and colleagues[209] demonstrated that continuous measures of alexithymic, but not autistic, traits are predictive of poorer facial emotion recognition from static face images. Furthermore, when groups are matched in terms of alexithymia, autistic and non-autistic adults perform comparably with respect to the recognition of emotion[209]. Similarly, Milosavljevic et al[213] demonstrated lower emotion recognition scores - again from static face images - for autistic adolescents high in alexithymia relative to those low in alexithymia. Consequently, Bird and Cook[207] proposed 'the alexithymia hypothesis': autistic individuals' difficulties in emotion-processing, including facial emotion recognition, are caused by co-occurring alexithymia not ASD.

To date, the majority of studies that have reported that atypical facial emotion processing is related to alexithymia, not autism, have focused on the recognition of emotion from *static* face images, and have thus overlooked the inherently dynamic nature of facial expressions[248,249]. Dynamic faces carry both spatial information about the configuration of facial features relative to each other and information about the kinematics (e.g., speed) of movement of facial features[336]. Recent developments in the face-processing literature emphasise the importance of both kinematic and spatial cues in *non-autistic* facial emotion recognition. Most notably, Sowden and colleagues[239] manipulated point-light face (PLF) stimuli (a series of white dots on a black background that convey biological motion and eliminate contrast, texture, colour and luminance cues) such that expressions of happiness, anger and sadness were reproduced at 50%, 100% and 150% of their normal speed, and at 50%, 100% and 150% of their normal range of spatial movement (e.g., at the 150% level a smile would be 50% bigger / more exaggerated than normal). Sowden and colleagues[239] found that the emotion recognition accuracy of non-autistic participants was modulated as a function of both spatial and kinematic manipulation. Specifically, when expressions were reduced in their speed and spatial extent (i.e., at the 50% level), participants were less accurate in their labelling of angry and happy expressions and more accurate for sad expressions. Conversely, when expressions were played with exaggerated spatial movement and greater speed (i.e., at the 150% level), participants displayed higher accuracy for angry and happy expressions and lower accuracy for sad expressions[239]. Thus, accuracy for labelling high arousal emotions (happy and angry) is improved when the stimulus is faster and more spatially exaggerated, whereas labelling of low arousal emotions (sad) is impaired. Recent literature therefore highlights that, for non-autistic individuals, both spatial and kinematic facial cues contribute to emotion recognition accuracy.

Although dynamic information is particularly important in real life processing of facial expressions[337], to the best of our knowledge, there are no studies that have investigated autistic versus non-autistic recognition of emotion *from dynamic facial motion stimuli* (e.g., PLFs) whilst controlling for the influence of alexithymia. There are, however, some studies that have compared autistic and non-autistic processing of full (i.e., not degraded) dynamic facial expressions without controlling for alexithymia. For example, Sato and colleagues[338] demonstrated that, for non-autistic adults, reducing the movement speed of facial morph stimuli[1b] reduced naturalness ratings, however, for autistic adults the effect of speed on naturalness ratings was significantly weaker. Sato and colleagues' results thus demonstrate differences between autistic and non-autistic adults in the effects of manipulating facial kinematics. However, it remains to be seen whether these differences would persist if the groups were matched in terms of alexithymia. To the best of our knowledge, only one study has examined the contribution of autistic *and* alexithymic traits to dynamic emotion recognition[212]. The findings of this study support the alexithymia hypothesis: high alexithymic, but not autistic, traits were associated with less accurate facial expression recognition[212]. However, this study, conducted by Ola and Gullon-Scott, has two important limitations. First, only female participants were recruited. Since autistic males comprise three quarters of the ASD population[339], and likely differ in behavioural phenotype[250-253,340], one must be cautious about extrapolating the findings to autistic males. Second, Ola and Gullon-Scott did not recruit a non-autistic control group. Consequently, the authors were not able to explore whether autistic versus non-autistic group differences in dynamic emotion recognition remain after controlling

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[b] Facial morph stimuli were constructed by successively presenting 26 images from a neutral (0%) to full emotional (100%) expression with an increase of 4% in emotion from one image to the next. By presenting the images in this way, it gave the illusion of a dynamic emotional expression. The speed of playback was then manipulated to allow the researchers to test their hypotheses.

for alexithymia. That is, although Ola and Gullon-Scott were able to show that *some* difficulties with emotion recognition from dynamic stimuli were associated with alexithymia, one cannot conclude from this study that there are *no* differences with respect to emotion recognition from dynamic stimuli that are specifically associated with ASD.

The primary aim of the current study was to investigate whether autistic and non-autistic adults would exhibit differences in the recognition of emotion from facial motion cues when the groups were matched in terms of alexithymia. To address this aim, we employed the paradigm developed by Sowden and colleagues[239] which uses PLF stimuli to represent emotional expressions in terms of the movement of facial landmarks. More specifically, male and female autistic and non-autistic adults rated the emotion expressed by PLF stimuli that had been manipulated such that expressions of happiness, anger and sadness were reproduced at 50%, 100% and 150% of their normal speed and spatial extent. The groups were matched in terms of their scores on a self-report measure of alexithymia. We predicted that emotion recognition accuracy would be affected by both kinematic and spatial manipulation and that these effects would not interact with group, but rather that Bayesian statistics would provide support for the null hypothesis that the alexithymia-matched groups perform comparably. Given that we had considerable variation in alexithymic traits, a secondary aim of our study was to explore whether the effects of the spatial and kinematic manipulation on emotion recognition accuracy covaried with scores on the self-report alexithymia measure.

2.2. Method

2.2.1. Participants

The chosen sample size is based on an *a priori* power analysis conducted using GLIMMPSE[341], which focused on replicating the primary results from Sowden et al[239] in the control group (the emotion x spatial and emotion x kinematic interactions). Using data from Sowden et al[239], 8 participants are required in the control group in order to have 95% power to detect an effect size of 0.70 (η_P^2) at alpha level 0.01 for the emotion x spatial interaction. Moreover, 11 participants are required in the control group in order to have 95% power to detect an effect size of 0.53 (η_P^2) for the emotion x kinematic interaction at alpha level 0.01. However, Button et al[2013] argue that effect size estimates are commonly inflated ("the winners curse"), and that there is "a common misconception that a replication study will have sufficient power to replicate an initial finding if the sample size is similar to that in the original study". Accordingly, we planned to recruit a larger number of participants (N=30 per group; almost triple the largest sample size generated in our power calculations), in order to obtain adequate power. We pre-registered this sample size via the Open Science Framework (https://osf.io/kpefz).

60 individuals, 31 with an ASD diagnosis and 29 non-autistic controls, participated in the study (See Appendix 1.1 for ethnicity information). Participants were matched for age, gender, non-verbal reasoning (NVR; as measured by the Matrix Reasoning Item Bank; MaRs-IB[343]) and alexithymia (as measured by the 20-item Toronto Alexithymia Scale; TAS-20[344]). The ASD group had significantly higher Autism Quotient (AQ[304]) scores (see Table 2.1). The level of autistic characteristics of those in the ASD group was assessed using the Autism Diagnostic Observation Schedule (version 2, ADOS-2[345]). The mean total ADOS-2 score in the ASD group was 10.59 (see Appendix 1.2 for information on the quantity of participants that met criteria for diagnosis). The MaRs-IB was used to match participants on the basis that the PLF task relies on non-verbal reasoning ability and, with respect to participant matching, task specific measures of intelligence/ability have been argued to be more appropriate than general measures[346]. A total of four participants (three in the ASD group and one in the control group)

had AQ or TAS-20 scores over two standard deviations from their group mean. Since the general pattern of results was unaffected by their removal, these participants are included in the final analysis.

Table 2.1.

Means, standard deviations and group differences of participant characteristics

	Control group (n=29)	ASD group (n=31)	Significance
Gender	11 Female, 17 Male, 1 Other	14 Female, 16 Male, 1 Other	p= .850
Age	28.81 (9.54)	30.14 (9.08)	p= .581
NVR	62.91 (15.17)	57.05 (17.90)	p= .178
TAS-20	55.66 (13.57)	59.74 (13.14)	p= .241
AQ	19.86 (7.44)	32.52 (10.21)	p< .001
ADOS-2	N/A	10.32(4.76)	N/A

Note. In the central columns, means are followed by standard deviations in parentheses.

Twenty-two of the 31 ASD participants were recruited via an existing autism research database kept by the Birmingham Psychology Autism Research Team (B-PART). The control and remaining nine ASD participants were recruited via social media (Facebook and Twitter) and Prolific – an online recruitment platform. All participants in the ASD group had previously received a clinical diagnosis of ASD from a qualified clinician.

2.2.2. Materials and stimuli

PLF stimuli

The PLF task was an adapted version of that developed by Sowden and colleagues[239] which was re-programmed in Gorilla.sc[347] to facilitate online testing. The same instructions, stimulus videos, and rating scales were used as in the original study. The stimulus videos comprised dynamic PLF stimuli, created from videos of four actors (two male, two female) verbalising sentences ("My name is John and I'm a scientist") whilst posing three target emotions (angry, happy and sad). PLFs were adapted (see Sowden et al[239] for further detail) to achieve three spatial movement levels, ranging from decreased to increased spatial movement

(S1: 50% spatial movement; S2: 100% spatial movement; S3: 150% spatial movement), and three kinematic levels, ranging from reduced to increased speed (K1: 50% original stimulus speed; K2: 100% original stimulus speed; K3 – 150% of the original stimulus speed). Consequently, there were 9 manipulations per emotion (e.g., (1) S1, K1, (2) S2, K1, (3) S3, K1, (4) S1, K2, (5) S2, K2, (6) S3, K2, (7) S1, K3, (8), S2, K3, (9) S3, K3).

Autistic traits

The level of autistic traits of all ASD and control participants was assessed via the 50-item Autism Quotient[304]. Scores on this self-report scale range from 0 to 50, with higher scores corresponding to higher levels of autistic characteristics. The AQ assesses five different areas relevant for ASD traits (attention switching, attention to detail, communication, social skill and imagination). The AQ has been widely used in both the general and the autistic population[348,349], and boasts strong psychometric properties, including internal consistency ($\alpha \geq 0.7$) and test-retest reliability ($r \geq 0.8$)[350]. The AQ also had good internal consistency here ($\alpha = 0.86$).

Alexithymic traits

The level of alexithymic traits was measured via the Toronto Alexithymia Scale[344]. This self-report scale comprises 20 items rated on a five-point Likert scale (ranging from 1, strongly disagree, to 5, strongly agree). Scores on the TAS-20 can range from 20 to 100, with higher scores indicating higher levels of alexithymia. The TAS-20 is the most popular tool for assessing alexithymia[149] and has good internal consistency ($\alpha \geq 0.7$) and test-retest reliability ($r \geq 0.7$)[344,351]. The TAS-20 also had good internal consistency here ($\alpha = 0.82$).

Non-verbal reasoning

Non-verbal reasoning was assessed via the Matrix Reasoning Item bank (MaRs-IB)[343]. Each item in the MaRs-IB consists of a 3 x 3 matrix. Eight of the nine available cells in the matrix are filled with abstract shapes, and one cell in the bottom right-hand corner is left empty.

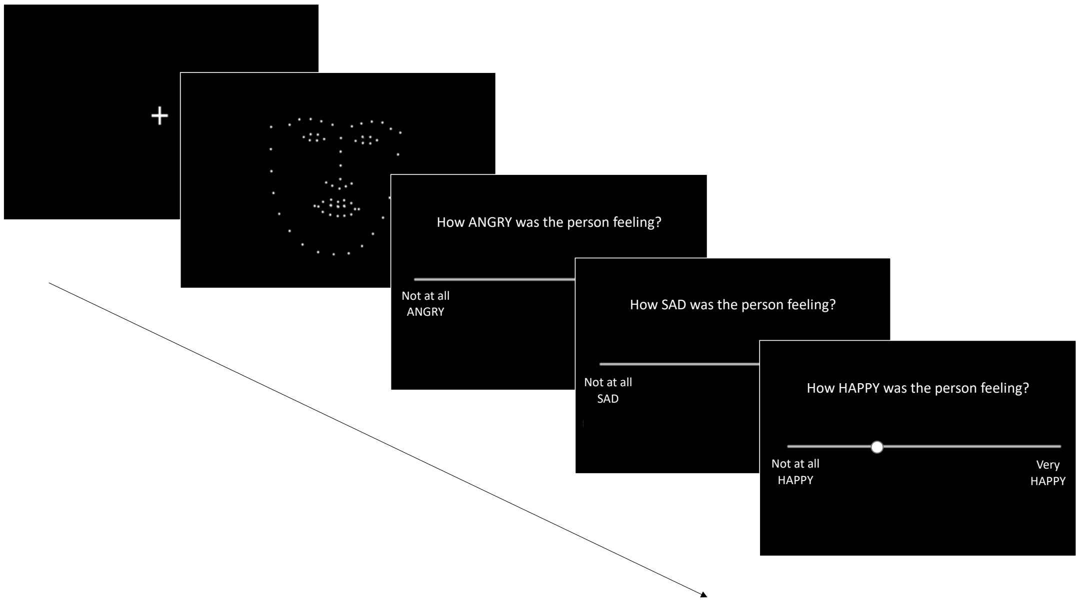
Participants are required to complete the matrix by selecting the missing shape from four possible options. In order to correctly identify the missing shape, participants have to deduce relationships between the shapes in the matrix (which vary in shape, colour, size and position). When participants select an answer, they move on to the next item. If participants do not provide a response within 30 seconds, they continue to the next item without a response. The MaRs-IB assessment lasts 8 minutes regardless of how many trials are completed. There is a total of 80 different items in the MaRs-IB, however participants are not required (or expected) to complete all 80 items within the 8 minutes. If a participant completed all 80 items within 8 minutes, the items were presented again but the responses to these were not analysed (following the procedure established by Chierchia and Fuhrmann et al[343]). The MaRs-IB has been shown to have acceptable internal consistency (Kuder-Richardson 20 ≥ 0.7) and test-retest reliability ($r \geq 0.7$)[343].

2.2.3. Procedures

Following a pre-registered design (see https://osf.io/kpefz)**,** participants first completed the questionnaires (demographics followed by AQ, followed by TAS-20) and then moved on to the PLF task. Each trial in this task began with the presentation of a stimulus, which comprised a silent PLF video of an actor expressing one of 3 emotions whilst saying a sentence at one of the 3 spatial and 3 kinematic levels[239]. After watching the video, participants were asked to rate how *angry, happy* and *sad* the person was feeling[239]. Participants made their ratings on a visual analogue scale, with one end representing 'Not at all *angry/happy/sad*' and the opposite end representing 'Very *angry/happy/sad*'[239]. Individuals were asked to make ratings for all three target emotions (angry, happy and sad) on scales, which were presented on screen in a random order, after each PLF video[239]. Each trial took approximately 25 seconds to complete. Participants completed 3 practice trials (at the S2 and K2 level) and then 108 randomly ordered experimental trials (12 per condition) across three blocks. Participants were invited to take a break between blocks. The structure of each trial is displayed in Figure 2.1.

Figure 2.1.

Example of one trial in the PLF Emotion Recognition task



Note. The fixation cross display is presented for 500ms at the start of each trial. The average length of a stimulus video was approximately 7 seconds. Rating scales remained on screen until participants had rated the stimulus and pressed the space bar

Following PLF task completion, participants completed the Matrix Reasoning Item Bank (MaRs-IB)[343].

Participants completed all tasks online using Google Chrome or Mozilla Firefox on a computer or laptop. The frame rate (in frames per second; FPS) of their devices was measured to ensure that the quality/fluidity of the stimulus videos was not degraded. All participants' frame rates were 60 FPS or higher with one exception at 50 FPS. When we ran all analyses with and without the 50 FPS participant, treating them as a potential outlier, the pattern of results was unaffected. Therefore, this participant was included in all analyses.

2.2.4. Statistical Analysis

The three emotion rating responses for each trial were transformed into magnitude scores from 0 to 10 (with 0 representing a response of 'Not at all' and 10 representing 'Very') to 3 decimal places. Emotion recognition accuracy scores were calculated as the correct emotion rating minus the mean of the two incorrect emotion ratings[c]. For instance, for a trial in which an angry PLF was presented, the mean rating of the two incorrect emotions (happy and sad) was subtracted from the correct emotion (angry). Thus, emotion recognition accuracy reflects how well an individual can distinguish whether an incoming expression is angry versus happy versus sad. As discussed, our PLF stimuli were created by recording four actors verbalising sentences while posing anger, happiness, and sadness, respectively (see [239]). Although these actors were instructed to produce discrete angry, happy, and sad facial expressions, it is important to note that we cannot guarantee that they did not inadvertently produce mixed emotional expressions. As such, one may argue that there is no objective "ground-truth" in the emotions that are depicted in the PLF expressions. This limitation is not confined to the PLF expressions used here, but to all facial expression stimuli used in the literature. This has led researchers to call for emotion recognition accuracy to be considered as a form of agreement between the expressor (i.e., our actors) and perceiver[46]. Therefore, here we conceptualise emotion recognition accuracy as the degree of agreement between the PLF actor and the participants in the present study.

[c] Many of the studies that have investigated the emotion recognition ability of autistic individuals have used forced-choice paradigms in which there is a binary (correct; 1, or incorrect; 0) accuracy score for each trial. In order to facilitate comparison of our results to those studies, we also completed a binary accuracy analysis, which yielded similar results (see Appendix 1.3). In this analysis, for each trial, participants scored 1 when they gave the highest rating to the correct emotion, and 0 when they rated either of the incorrect emotions higher than the correct emotion.

To test our first hypothesis, we submitted these accuracy scores to a 2 x 3 x 3 x 3 Analysis of Variance (ANOVA) with the between-subjects factor *group* (ASD, control) and the within-subjects factors *emotion* (happy, angry, sad), *stimulus spatial level* (S1, S2, S3), and *stimulus kinematic level* (K1, K2, K3). This analysis has the potential to reveal differences between the groups in their accuracy of emotion recognition from facial motion cues. It is possible, however, that two groups could have comparable accuracy scores but different patterns of ratings. For example, an accuracy score of 2 for an angry stimulus could relate to an anger magnitude rating of 4 and happy and sad ratings of 2, or an anger rating of 4, happy rating of 0, and a sad rating of 4. To more sensitively pick up on any differences between groups we used magnitude as the DV and conducted a 2 x 3 x 3 x 3 x 3 ANOVA with the between subjects factor *group* (ASD, control) and the within-subjects factors *emotion* (happy, angry, sad), *stimulus spatial level* (S1, S2, S3), *stimulus kinematic level* (K1, K2, K3) and *rating* (happy, angry, sad).

To explore whether the effects of the spatial and kinematic manipulation on emotion recognition accuracy covaried with alexithymia scores we employed multiple regression analyses. More specifically, we applied a sqrt transformation to all ordinal factors of interest (age, NVR, AQ, TAS-20), computed z-scores for the transformed data, and submitted the transformed z-scored data, along with the nominal predictor *gender,* to multiple regression analyses. The effect of the spatial manipulation (defined as the difference in accuracy between S3 and S1), the effect of the kinematic manipulation (defined as the difference in accuracy between K3 and K1), mean recognition accuracy, and accuracy for angry videos at the normal level (S2, K2) were used as the DVs for each of these analyses. In addition, in order to explore whether autistic and/or alexithymic traits predicted the magnitude of correct and incorrect ratings, we constructed two linear mixed effects models with ratings for angry facial motion at the normal level, and ratings across all emotions and levels of the spatial and kinematic manipulation, as the DVs respectively. For all analyses, we used a $p = .05$ significance threshold to determine whether to accept or reject the null hypothesis. The frequentist approach was supplemented with the calculation of Bayes Factors, which quantify the relative evidence for one theory or model over another. For all Bayesian analyses, we followed the classification scheme used in JASP[352] : BF_{10} values between one and three represent weak evidence, between three and ten moderate evidence, and greater than ten strong evidence, for the experimental hypothesis. For all Bayesian ANOVAs, the default Uniform prior was used. For all Bayesian linear regressions, the default Jeffreys-Zellner-Siow prior was used [r scale = 0.354].

2.3. Results

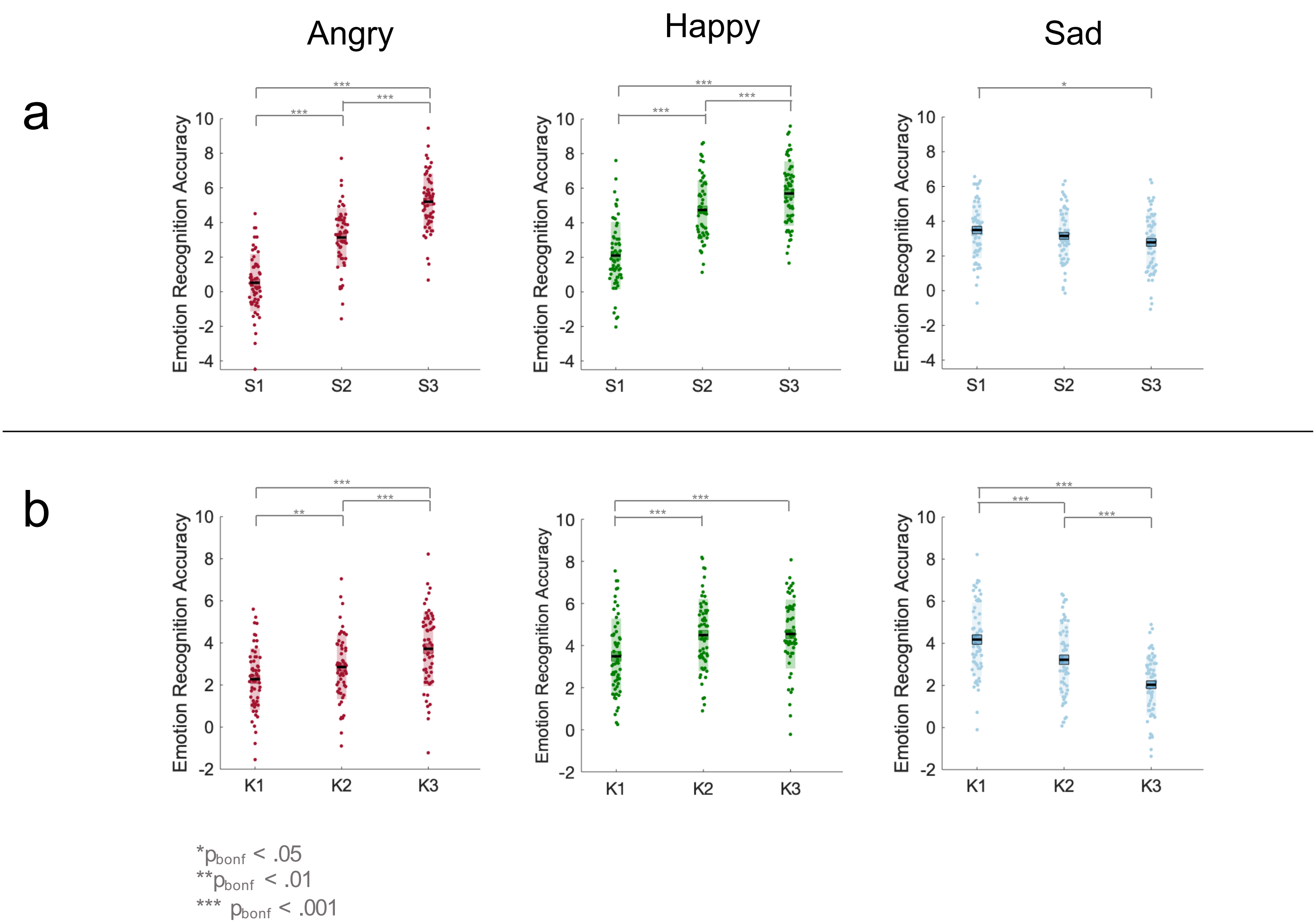
Our primary hypothesis was that emotion recognition accuracy would be affected by both kinematic and spatial manipulation and that these effects would not interact with group. To test this hypothesis, we conducted a mixed 2 x 3 x 3 x 3 ANOVA with the between-subjects factor *group* (ASD, control) and the within-subjects factors *emotion* (happy, angry, sad), *stimulus spatial level* (S1, S2, S3), and *stimulus kinematic level* (K1, K2, K3). This analysis revealed a significant main effect of emotion [$F(2,116) = 17.79$, $p < .001$, $\eta_P^2 = .24$, $BF_{10} = 1.03e^{15}$; see Appendix 1.4], a main effect of spatial level [$F(2,116) = 259.57$, $p < .001$, $\eta_P^2 = .82$, $BF_{10} = 9.05e^{57}$; see Appendix 1.4] which was qualified by an emotion x spatial interaction [$F(4,232) = 88.42$, $p < .001$, $\eta_P^2 = .60$, $BF_{10} = 7.53e^{58}$], and an emotion x kinematic interaction [$F(4,232) = 53.90$, $p < .001$, $\eta_P^2 = .48$, $BF_{10} = 1.90e^{20}$]. Furthermore, this analysis revealed a significant four-way emotion x spatial x kinematic x group interaction [$F(8,464) = 2.438$, $p < .05$, $\eta_P^2 = .04$, $BF_{10} = 0.07$]. Note that no kinematic x group interaction was found [$p = .538$, $BF_{10} = 0.02$], suggesting that autistic and control participants exhibit similar patterns of accuracy across the kinematic levels. Below, in order to shed light on the effects of the spatial and kinematic manipulations, we first unpack the emotion x kinematic and emotion x spatial interactions. Subsequently we fully unpack the emotion x spatial x kinematic x group interaction.

In line with Sowden et al[239], we observed an emotion x spatial interaction [$F(4,232) = 88.42$, $p < .001$, $\eta_P^2 = .60$, $BF_{10} = 7.53e^{58}$]. Post-hoc repeated measures ANOVAs revealed that whilst the effect of the spatial manipulation was present for all three emotions (all $F > 7.00$, all $p < .01$), the direction of the effect varied between high and low arousal emotions: recognition scores for angry and happy facial motion were highest for 150% spatial extent (S3) [angry mean (Standard Error of the Mean; SEM) = 5.21(.21); happy mean(SEM) = 5.70(.24)], followed by 100% spatial extent (S2) [angry mean(SEM) = 3.15(.22); happy mean(SEM) = 4.75(.23)], and finally 50% spatial extent (S1) [angry mean SEM) = 0.53(.22); happy mean(SEM) = 2.10(.25)]. In contrast, for sad facial motion, recognition scores were highest for S1 [sad mean(SEM) = 3.50(.22)], lowest for S3 [sad mean(SEM) = 2.78(.22)] and intermediate for S2 [sad mean(SEM) = 3.15(.20)]. This pattern matches the results reported by Sowden et al., (2021) for non-autistic participants. The emotion recognition accuracy scores for each emotion across the spatial levels can be seen in Figure 2.2 (a).

In addition, our analysis identified an emotion x kinematic interaction [$F(4,232) = 53.90$, $p < .001$, $\eta_P^2 = .48$, $BF_{10} = 1.90e^{20}$]. Whilst there was a main effect of the kinematic manipulation for all three emotions (all $F > 20$, all $p < .001$), the direction of the effect differed between high and low arousal emotions. For angry and happy facial motion, emotion recognition improved with increasing speed [angry: K1 mean(SEM) = 2.28(.19); K2 mean(SEM) = 2.87(.19); K3 mean(SEM) = 3.73(.23); happy: K1 mean(SEM) = 3.50(.23); K2 mean(SEM) = 4.50(.22); K3 mean(SEM) = 4.55(.21)]. For sad facial motion, emotion recognition improved as speed decreased [K3 mean(SEM) = 2.03(.19); K2 mean(SEM) = 3.21(.22); K1 mean(SEM) = 4.18(.23)]. This pattern of results also matches the findings from Sowden et al[239]. The emotion recognition accuracy scores for each emotion across the kinematic levels can be seen in Figure 2.2 (b).

Figure 2.2.

Mean accuracy scores, for all participants, for each emotion across the spatial (panel a) and kinematic (panel b) levels.

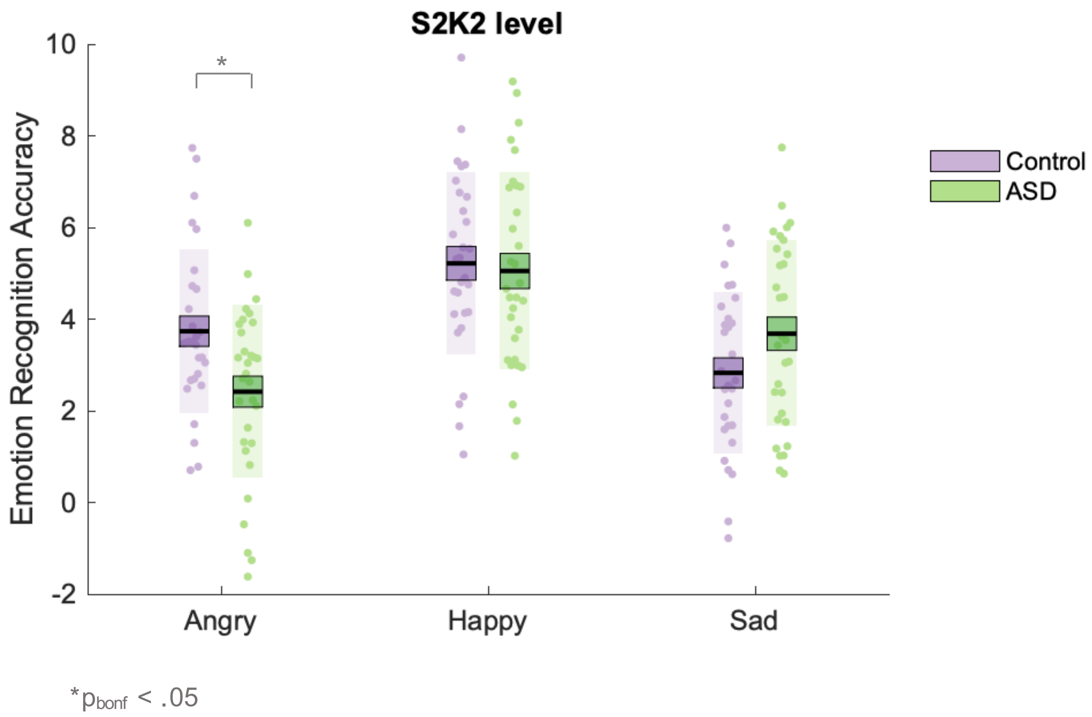


Note. The black line represents the mean, the shaded region represents the standard deviation, the coloured box represents 1 standard error around the mean and the dots are individual datapoints.

In order to unpack the significant four-way interaction, we conducted post-hoc 2 x 3 x 3 (group, emotion, kinematic) ANOVAs for each spatial level. This analysis revealed a significant emotion x kinematic x group interaction at the S2 [$F(4,232) = 4.53$, $p < 0.01$, $\eta_P^2 = .07$, $BF_{10} = 5.92$] but not S1 [$p = .265$, $BF_{10} = 0.09$] or S3 [$p = .208$, $BF_{10} = 0.09$] level. To unpack this emotion x kinematic x group interaction at the S2 level, we conducted separate post-hoc ANOVAs for each kinematic level at the 100% (S2) spatial level. This analysis revealed a significant emotion x group interaction at the K2 [$F(2,116) = 6.48$, $p < .01$, $\eta_P^2 = .10$, $BF_{10} = 17.09$] but not K1 [$p = .244$, $BF_{10} = 0.32$] or K3 [$p = .082$, $BF_{10} = 0.82$] level. Bonferroni-corrected post-hoc independent sample t-tests revealed that control, relative to ASD, participants had higher accuracy for angry facial motion at the 100% spatial (S2) and speed (K2) level [$t(58) = 2.78$, $p_{bonf.} < .05$, mean difference = 1.48, $BF_{10} = 6.09$]. There were no significant group differences in emotion recognition accuracy for happy [$p = .757$, $BF_{10} = 0.27$] or sad [$p = .085$, $BF_{10} = 0.93$] videos at the S2K2 level. Thus, the groups significantly differed in accuracy for angry PLFs that were not spatially or kinematically manipulated. The mean emotion recognition accuracy scores across each emotion for control and ASD participants at the S2K2 level are shown in Figure 2.3.

Figure 2.3.

Accuracy at the S2, K2 level, as a function of emotion



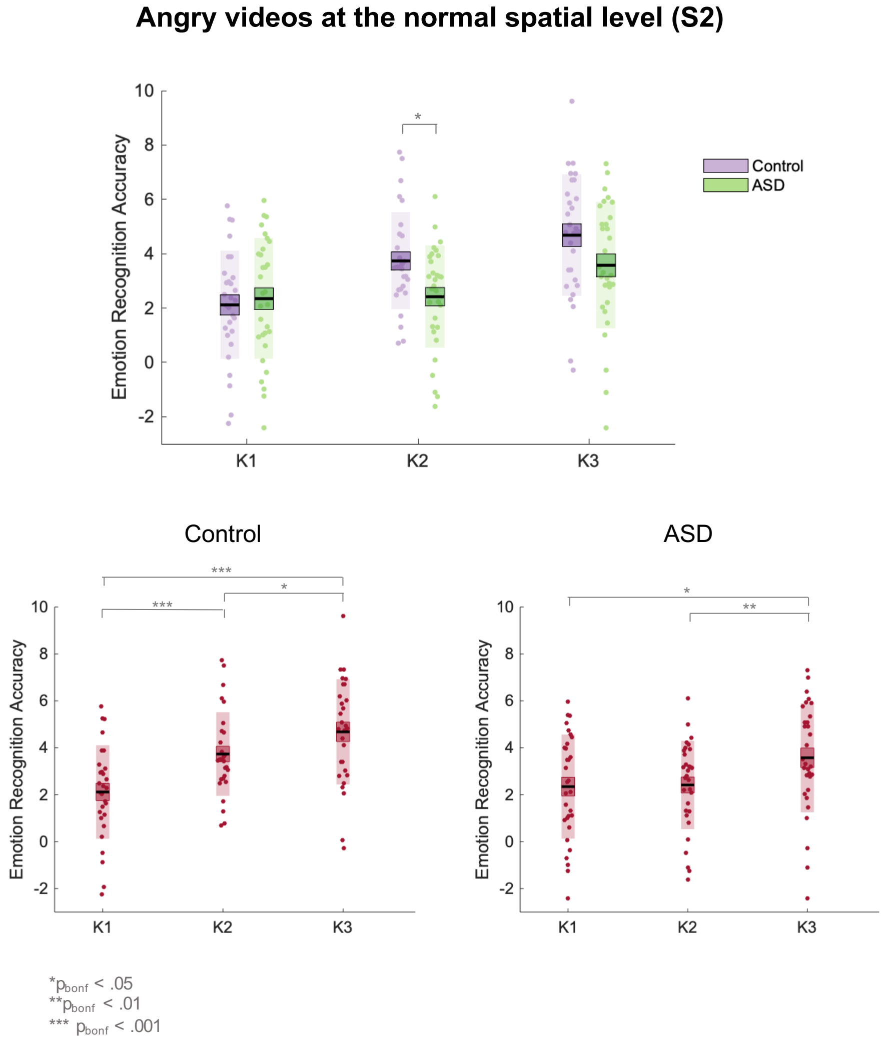
Note. Control in lilac, ASD in green. The black line represents the mean, the coloured box represents the standard error of the mean, the shaded region represents the standard deviation, and the dots are individual datapoints.

To further unpack the emotion x kinematic x group interaction at the S2 level, we conducted separate post-hoc ANOVAs for each emotion at the S2 level. This analysis identified a significant kinematic x group interaction for angry [$F(2,116) = 4.59$, $p < .05$, $\eta_P^2 = .07$, $BF_{10} = 3.49$] but not happy [$p = .070$, $BF_{10} = 0.95$] or sad [$p = .123$, $BF_{10} = 0.53$] PLFs. Therefore, for angry videos at the normal spatial level, the effect of the kinematic manipulation varied as a function of group. Bonferroni-corrected paired sample t-tests demonstrated that whilst the control group exhibited increasing accuracy across all kinematic levels [K1-K2: $t(28) = -4.31$, $p_{bonf} < .001$, mean difference = -1.62, $BF_{10} = 153.77$; K2-K3: $t(28) = -2.86$, $p_{bonf} < .05$, mean difference = -0.95, $BF_{10} = 5.52$], the ASD group only showed improvement from the K2 to K3

[$t(30) = -3.46$, $p_{bonf} < .01$, mean difference = -1.16, $BF_{10} = 21.10$] and not K1 to K2 [$p = .865$, $BF_{10} = 0.19$]. Furthermore, the groups did not significantly differ at K1 ($F(1,58) = .18$, $p > .05$) or K3 ($F(1,58) = 3.53$ $p > .05$) but at K2, controls out-performed autistic participants ($F(1,58) = 7.75$, $p < 0.01$, $\eta_P^2 = .12$). These results suggest that, whilst controls improved in their accuracy for angry PLF stimuli across each level of increasing kinematic manipulation, for autistic participants, only the most extreme (K3) level of the kinematic manipulation resulted in an accuracy boost. The mean accuracy scores for angry videos across the kinematic levels (at the unmanipulated S2 level) for control and ASD participants are shown in Figure 2.4.

Figure 2.4.

Mean accuracy scores for angry videos at the S2 level for control and ASD participants across the kinematic levels



Note. The black line represents the mean, the coloured box represents the standard error of the mean, the shaded region represents the standard deviation, and the dots are individual datapoints.

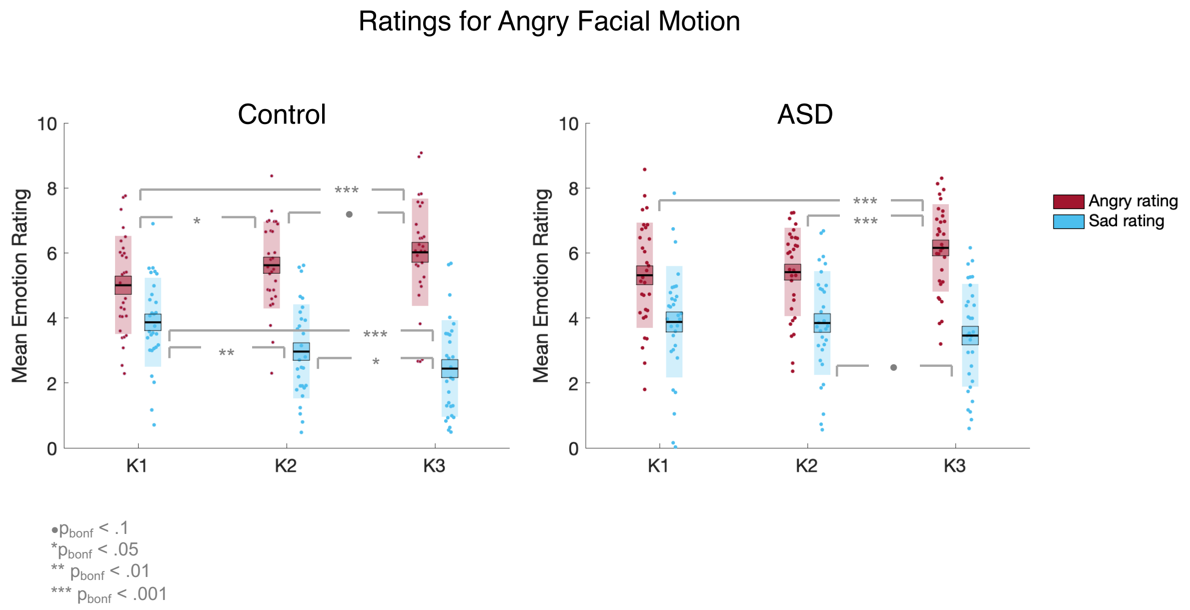
In order to compare the magnitude of the ratings between groups, we conducted a mixed 2 x 3 x 3 x 3 x 3 ANOVA with the between subjects factor *group* (ASD, control) and the within-subjects factors *emotion* (happy, angry, sad), *stimulus spatial level* (S1, S2, S3), *stimulus* *kinematic level* (K1, K2, K3) and *rating* (happy, angry, sad). This analysis revealed a significant main effect of emotion [$F(2,116) = 34.86$, $p < .001$, $\eta_P^2 = .38$], spatial level [$F(2,116) = 50.52$, $p < .001$, $\eta_P^2 = .47$], kinematic level [$F(2,116) = 3.51$, $p < .05$, $\eta_P^2 = .06$] and rating [$F(2,116) = 3.592$, $p < .05$, $\eta_P^2 = .06$, $BF_{10} = 76$], as well as emotion x rating [$F(4,232) = 489.95$, $p < .001$, $\eta_P^2 = .89$], spatial x rating [$F(4,232) = 64.26$, $p < .001$, $\eta_P^2 = .53$], kinematic x rating [$F(4,232) = 49.08$, $p < .001$, $\eta_P^2 = .46$], emotion x spatial x rating [$F(8,464) = 111.13$, $p < .001$, $\eta_P^2 = .66$], emotion x kinematic x rating [$F(8,464) = 12.02$, $p < .001$, $\eta_P^2 = .17$], kinematic x rating x group [$F(4,232) = 2.79$, $p < .05$, $\eta_P^2 = .05$] and spatial x kinematic x rating x group [$F(8,464) = 2.76$, $p < .05$, $\eta_P^2 = .05$] interactions. All interactions and main effects are unpacked in Appendix 1.5.

In addition, this analysis revealed an emotion x kinematic x rating x group interaction which approached significance [$F(8,464) = 1.90$, $p = .058$, $\eta_P^2 = .03$]. Since this interaction potentially offers further insight about the between group difference in anger recognition, we unpack it in full here. Post-hoc 2 x 3 x 3 ANOVAs (group x kinematic x rating) for each of the emotional videos revealed a significant kinematic x rating x group interaction for angry [$F(4,232) = 4.26$, $p < .01$, $\eta_P^2 = .07$, $BF_{10} = 0.61$] but not happy [$p = .687$, $BF_{10} = 0.03$] or sad [$p = .122$, $BF_{10} = 0.09$] facial motion. Importantly, post-hoc ANOVAs revealed that for control participants, speeding up angry facial motion (regardless of the spatial level) improves accuracy by increasing ratings of anger [$F(2,56) = 15.39$, $p < .001$, $\eta_P^2 = .36$, $BF_{10} = 3344.71$] and lowering ratings of sadness [$F(2,56) = 24.15$, $p < .001$, $\eta_P^2 = .46$, $BF_{10} = 374155.73$] across *all* levels of the kinematic manipulation [angry ratings K1-K2: $t(28) = -3.17$, $p < .01$, mean difference = -0.62, $BF_{10} = 10.71$; angry ratings K2-K3: $t(28) = -2.24$, $p < .05$, mean difference = -0.40, $BF_{10} = 1.67$; sad ratings K1-K2: $t(28) = 3.91$, $p = .001$, mean difference = 0.90, $BF_{10} = 58.34$; sad ratings K2-K3 $t(28) = 2.74$, $p < .05$, mean difference = 0.52, $BF_{10} = 4.34$] (however, note that after Bonferroni-correction, the difference in angry ratings for angry facial motion between K2 and K3 became non-significant; $p = .100$; see Figure 2.5).

For autistic participants, speeding up angry facial motion also improved accuracy by increasing ratings of anger [$F(2,60) = 12.18$, $p < .001$, $\eta_P^2 = .29$, $BF_{10} = 551.72$], however this effect was driven by an increase from the 100% to 150% level [$t(30) = -5.24$, $p = .001$, mean difference = -0.75, $BF_{10} = 1792.14$], and not the 50% to 100% level [$p = .636$, $BF_{10} = 0.21$]. In addition, we found that there was a main effect of kinematic level for sad ratings that approached significance [$F(2,60) = 2.89$, $p = .063$, $\eta_P^2 = .09$, , $BF_{10} = 0.90$]. Importantly, sad ratings only decreased from 100% to 150% speed [$t(30) = 2.32$, $p < .05$, mean difference = 0.39, $BF_{10} = 1.94$] and not from 50% to 100% speed [$p = .877$, $BF_{10} = 0.19$] (however, note that after Bonferroni-correction, the difference in sad ratings for angry facial motion between K2 and K3 became non-significant; $p = .081$; see Figure 2.5). Consequently, we primarily observe differences in the accuracy of anger recognition between our ASD and control groups because, for the ASD group, speeding up angry facial motion only reduces confusion between angry and sad ratings when the speed is increased from 100 to 150% (not 50 to 100%). In contrast, for the control group increasing the speed of angry facial motion from 50 to 100% *and* from 100 to 150% reduces confusion between anger and sadness ratings.

Figure 2.5.

Mean angry and sad ratings given by control and ASD participants for angry facial motion across the kinematic levels



Note. The black line represents the mean, the coloured box represents the standard error of the mean, the shaded region represents the standard deviation, and the dots are individual datapoints.

Multiple Regression Analyses

In addition, we aimed to explore whether variation in emotion recognition accuracy covaried with scores on our self-report alexithymia measure (TAS-20). To test whether autistic or alexithymic traits were predictive of the effect of the spatial and kinematic manipulations, we conducted two multiple regression analyses. For the first analysis, we used the effect of spatial manipulation (defined as the difference in accuracy between S3 and S1) as the dependent variable (DV) and AQ and TAS-20 as predictor variables. This analysis resulted in a non-significant model overall [$F(2,57) = .87$, $p = .425$], neither AQ [standardised $\beta = -.17$, $t(57) = -1.10$, $p = .274$] nor TAS-20 [standardised $\beta = .19$, $t(57) = 1.20$, $p = .236$] were significant predictors of the effect of the spatial manipulation. In the second analysis, we used the effect of the kinematic manipulation (defined as the difference in accuracy between K3 and K1) as the DV and AQ and TAS-20 as predictors. Again, this analysis resulted in a non-significant model [$F(2,57) = 1.63$, $p = .206$], neither AQ [standardised $\beta = .20$, $t(57) = 1.33$, $p = .189$] nor TAS-20 [standardised $\beta = .05$, $t(57) = .32$ $p = .752$] were significant predictors of the effect of the kinematic manipulation. We then conducted a third multiple regression with mean emotion recognition accuracy (across all trials) as the DV. Once again, neither AQ [standardised $\beta = -.19$, $t(57) = -1.24$, $p = .220$] nor TAS-20 [standardised $\beta = .12$, $t(57) = .81$, $p = .424$] were significant predictors of mean recognition accuracy and the overall model did not explain a significant amount of variance in the data [$F(2,57) = .78$, $p = .461$]. To explore the possibility that only extreme scores on the TAS-20 predict performance, we compared mean accuracy for alexithymic (i.e., TAS-20 $\geq$ 61) and non-alexithymic (i.e., TAS-20 $\leq$ 51) participants (according to the cut-off scores outlined by Bagby, Taylor & Parker[344]), excluding 'possibly alexithymic' individuals. An independent samples t-test confirmed that there was no significant difference in mean accuracy between these groups [$t(48) = -.18$, $p = .861$, mean difference = -.05, BF_{10}= 0.29].

Finally, building on our previous observation that the ASD and control groups differed in accuracy for angry facial motion at the normal (100%) spatial and speed level we conducted a multiple regression analysis to identify the extent to which autistic and alexithymic traits were predictive of accuracy for angry videos at the S2 and K2 levels. This analysis revealed that autistic [standardised $\beta = -.44$, $t(57) = -3.05$, $p < .01$], but not alexithymic [standardised $\beta = .22$, $t(57) = 1.54$, $p = .130$], traits were predictive of accuracy for angry facial motion at the normal spatial and speed level [overall model statistics: $F(2, 57) = 4.67$, $p < .05$, $R^2 = .141$]. Bayesian analyses, using a default prior [Jeffreys-Zellner-Siow prior; r scale = 0.354], revealed that AQ

[$BF_{inclusion} = 4.230$] was over 16 times more likely to be included in a model to predict accuracy for angry videos at the normal spatial and speed level than alexithymic traits [$BF_{inclusion} = 0.263$].

In order to ensure that AQ is not just a significant predictor of accuracy for angry expressions at the normal spatial and speed level due to variation across other co-variables (e.g., age, gender, and non-verbal reasoning), we completed an additional three-step forced entry hierarchical regression analysis following the procedures of Cook and Brewer et al[209]. In the first step, the demographic variables (gender, age and NVR) were entered into the model, which overall accounted for 16% of the variance in accuracy at the S2K2 level [$F(3,56) = 3.56$, $p < .05$, $R^2 = .160$]. Importantly, of the three demographic variables, only NVR was a significant predictor of accuracy for angry facial motion at the normal spatial and speed level [standardised $\beta = .35$, $t(56) = 2.79$, $p < .01$] (and not gender [standardised $\beta = .15$, $t(56) = 1.20$, $p = .233$] or age [standardised $\beta = - .01$, $t(56) = -.06$, $p = .950$]). In the second step, AQ was added [standardised $\beta = -.36$, $t(55) = -3,13$, $p < .01$], producing a statistically significant R^2 change [F change (1, 55) = 9.80, $p < .01$, R^2 change = .127]. Finally, when TAS-20 was entered into the model, the analysis revealed it was not a significant predictor of accuracy for angry facial motion at the normal level [standardised $\beta = .17$, $t(54) = 1.26$, $p = .214$] and resulted in a non-significant R^2 change [F change (1, 54) = 1.58, $p = .214$, R^2 change = .020; see Table 2.2]. Hence, this analysis demonstrated that autistic traits (and not alexithymic traits) were a significant predictor of accuracy for angry facial motion at the normal level (S2, K2) even after age, gender and NVR have been accounted for.

These analyses suggest that alexithymia accounts for very little variance in accuracy for angry facial motion at the normal (S2K2) level once autistic traits have been accounted for. However, since our autism and alexithymia measures were correlated [$R = .53$, $p < .001$], when alexithymia is entered into a multiple regression after autistic traits, it may not be a significant predictor due to collinearity. Consequently, we ran one further hierarchical regression, with the demographic variables entered in Step 1, alexithymia in Step 2 and autistic traits in Step 3. Alexithymia failed to significantly improve the model [F change (1, 55) = .31, p = .581, R^2 change = .005], explaining only 0.5% more variance than that explained by the demographic variables alone. Despite being highly correlated with alexithymia, autistic traits were again a significant predictor of accuracy for angry facial motion at the normal level [standardised β = -.45, t(54) = -3.33, p < .01] when added to the model in Step 3. Adding autistic traits at this step produced a statistically significant R^2 change [F change (1, 54) = 11.12, p < .01, R^2 change = .143], explaining an additional 14.3% of the variance in accuracy.

Table 2.2.

Results of the forced entry hierarchical regression for accuracy for angry videos at the normal spatial and speed level.

Model	R	R^2	Adjusted R^2	SEE	R^2 change	F change	Sig. F change
1	.400	.160	.115	1.82	.160	3.556	.020
2	.536	.287	.235	1.69	.127	9.798	.003
3	.554	.307	.243	1.68	.020	1.581	.214

Note. 1. predictors: age, gender, non-verbal reasoning; 2. predictors: age, gender, non-verbal reasoning, AQ; 3. predictors: age, gender, non-verbal reasoning, AQ, TAS-20.

The above results demonstrate that, compared to NVR, age, gender and alexithymia, autistic traits account for an additional 14.3% of the variance in the accuracy of anger recognition from motion cues at the normal (S2K2) level. In principle, autistic traits might contribute to anger recognition by modulating the magnitude of correct ratings (wherein lower AQ should be related to higher anger ratings for angry stimuli), the magnitude of incorrect ratings (wherein lower AQ should be related to lower happy and sad ratings for angry stimuli), or both. In addition, it is possible that alexithymic traits might contribute to correct and incorrect emotion ratings, but not emotion recognition accuracy (e.g., by contributing to both increased correct and incorrect emotion ratings). To explore these possibilities, and thereby shed light on the psychological mechanisms by which AQ negatively predicts anger recognition, we constructed a linear mixed effects model, predicting the magnitude of ratings with AQ score, TAS-20 score, the interaction between AQ score and rating type (correct vs. incorrect), and the interaction between TAS-20 and rating type (correct vs. incorrect). This analysis revealed a significant AQ x rating type interaction [$t(180) = 2.12$, $p < .05$], wherein AQ predicted incorrect [$t(59.89) = 3.36$, $p < .01$] but not correct [$p = .381$] emotion ratings for angry facial motion at the normal level; those with higher AQ gave higher incorrect emotion ratings (i.e., happy and sad) for angry facial motion at the normal level. Our analysis also identified that the relationship between TAS-20 and ratings (across correct and incorrect emotions) for angry facial motion at the normal level approached significance [$t(180) = 1.80$, $p = .074$]. Note that no TAS x rating type interaction was identified [$p = .288$].

The analyses reported above suggest that autistic traits contribute to anger recognition by modulating the magnitude of incorrect ratings, but not correct, ratings. In addition, these analyses revealed an interesting additional finding: alexithymic traits may be positively predictive of *both* correct and incorrect emotion ratings. Since the analyses reported above were restricted to the normal (S2K2) level for angry facial motion, next, we constructed one further linear mixed effects model (following the procedures outlined above) to investigate whether autistic and/or alexithymic traits are predictive of higher correct and incorrect emotion ratings across all emotions and levels of the spatial and kinematic manipulation. This analysis revealed that TAS-20 score was a significant positive predictor of the magnitude of ratings [$t(57.84) = 2.95$, $p < .01$], with those with higher alexithymia giving higher intensity (correct and incorrect) ratings across all emotions and levels of the spatial and kinematic manipulation. Importantly, the TAS x rating type interaction was not significant [$p = .125$], suggesting that alexithymic traits were predictive of *both* correct and incorrect emotion ratings. Our analysis also revealed that there was a significant AQ x rating type interaction [$t(4800.41) = 2.37$, $p < .05$]. In line with our previous analysis, AQ predicted incorrect [$t(49.02) = 2.24$, $p < .05$] but not correct [$p = .175$] emotion ratings, such that those higher in autistic traits gave higher incorrect ratings.

Therefore, our results suggest that whilst the level of autistic traits is predictive of accuracy for angry facial motion at the normal level (by positively predicting incorrect emotion ratings but not correct emotion ratings), alexithymic traits are not predictive of emotion recognition accuracy across emotions and manipulations but are positively predictive of *both* correct and incorrect emotion ratings.

2.4. Discussion

The current study tested whether autistic individuals, relative to alexithymia-matched controls, have greater difficulty recognising emotions from facial motion cues. We hypothesised that emotion recognition would vary as a function of kinematic and spatial manipulation and that these effects would not interact with diagnostic group, but rather Bayesian statistics would provide evidence that the groups perform comparably. We also aimed to explore whether the effects of spatial and kinematic manipulation on emotion recognition accuracy would covary with scores on a self-report alexithymia measure. In replication of Sowden et al[239], our results indicated that emotion recognition accuracy was affected by both spatial and kinematic manipulation. In addition, we identified that emotion recognition accuracy did not covary with alexithymia scores. In conflict with our hypothesis, we observed a significant emotion x spatial x kinematic x group interaction. Further unpacking this interaction revealed that autistic, relative to control, adults showed reduced recognition of angry facial motion at the normal (100%) spatial (S2) and speed (K2) level. Furthermore, whilst control participants improved in accuracy across all kinematic levels, autistic participants only benefitted from the speed increase from the normal (100%) to increased (150%) speed level. Exploration of the magnitude of ratings further demonstrated that, for non-autistic participants, speeding up angry PLFs improved accuracy through a combination of increasing anger ratings and decreasing sad ratings for both the 50-100% *and* 100-150% increase. In contrast, for autistic participants speeding up angry facial motion only increased anger ratings and decreased sad ratings between the 100% and 150% levels (not from 50-100%). In addition, multiple regression analyses revealed that autistic traits and NVR, but not age, gender or alexithymia, were significant predictors of recognition accuracy for angry facial motion at the normal spatial and speed level (where level of autistic traits was a negative predictor and NVR was a positive predictor). Although alexithymic traits were not associated with accuracy, they were associated with higher ratings for *both* the correct and incorrect emotions. Importantly, our results demonstrate that when autistic and control individuals are matched in terms of alexithymia there *are* group differences in recognition accuracy, though these are restricted to angry (not happy or sad) facial motion.

Of particular note is our finding that differences between autistic and control individuals are restricted to the recognition of anger from facial motion. This finding is in line with previous research suggesting that angry expressions are better recognised by non-autistic compared to autistic individuals[147,219-222] and is supported by meta-analytic evidence demonstrating greater differences between ASD and control groups in the recognition of angry compared to happy and sad expressions[191]. Importantly, however, some of these previous studies did not measure alexithymia[219-222] and in those that did, alexithymic and ASD traits were confounded[147], making it impossible to determine whether differences in anger recognition were attributable to alexithymia or ASD. The present study resolves this ambiguity and suggests that difficulties with recognising angry expressions at the 'normal' spatial and speed level are related to autism, not alexithymia.

An important observation is that in the current paradigm both groups performed equally well for slowed angry facial motion, but whilst the controls benefitted from the K1 to K2 speed increase (i.e., 50% to 100% speed), the autistic participants only benefitted from the K2 to K3 speed increase (i.e., accuracy only increased when the stimulus was played at 150% of normal speed). Our analysis of the magnitude of angry, happy and sad ratings for angry PLFs provided further insight into this effect: for non-autistic participants, speeding up angry PLFs from 50-100% speed *and* 100-150% improved accuracy through a combination of increasing anger ratings and decreasing sad ratings, thereby reducing the confusion between emotions. For autistic participants, speeding up angry facial motion also increased anger ratings and decreased sad ratings, however, this only happened between the 100% and 150% levels (not from 50-100%). This lack of a change in angry and sad ratings from 50 to 100% speed resulted in the autistic participants displaying significantly lower emotion recognition accuracy for angry facial motion at the 100% level. Further to this, the lack of a decrease in sad ratings may also explain why autistic traits were associated with higher incorrect emotion ratings for angry facial motion at the normal level (as found in our linear mixed effects model).

These findings also raise the possibility that autistic individuals may have a higher 'kinematic threshold' for perceiving anger from facial motion (i.e., an angry expression has to be moving quite quickly before it actually appears angry or *angrier* to ASD participants). This idea builds upon the findings of a previous study that used static photographic stimuli at varying expressive intensities (constructed by repeatedly morphing a full expression with a neutral expression to result in 9 intensity levels for each emotion) to estimate identification thresholds (the intensity at which an expression is identified correctly on two consecutive trials) for autistic and control participants. The authors found that autistic individuals had significantly higher identification thresholds than controls, meaning that a higher intensity was necessary before an expression appeared angry to ASD participants. Importantly, this study also found no significant group differences in identification thresholds for happiness or sadness[222]. Song and Hakoda's findings suggest that autistic individuals have a different identification threshold for *static* angry expressions[222]. For dynamic facial expressions, it may be that autistic and control individuals have a different *'kinematic identification threshold'* such that the expression must move more quickly (than would be required for control individuals) before it is identified as angry. Further research is necessary to investigate whether the group difference in recognising angry expressions at the S2K2 level is underpinned by a difference in kinematic identification thresholds.

Another (non-mutually exclusive) explanation for why the autistic individuals may have particular difficulty recognising angry expressions relates to movement production. Previous studies have documented differences between autistic and control participants in the production of facial expressions of emotion[146,147]. In our study, we used PLF videos that were made by filming four *non-autistic participants* posing different emotional states. Given that autistic and non-autistic individuals may produce different facial expressions and that one's own movement patterns influence the perception and interpretation of the movements of others[353-356], our autistic participants might have struggled to read emotion in our PLF videos because the expressions were dissimilar to expressions that they would have adopted themselves. To date, studies that have documented differences between autistic and control participants in the production of facial expressions of emotion have used non-autistic observer ratings as a measure of the quality of facial expression (i.e., from the perspective of a non-autistic rater autistic individuals produce expressions which appear “atypical”). Consequently, research has not yet identified what specifically is different about autistic and non-autistic facial expressions. Importantly, differences might be found in the final arrangement of facial features (i.e., spatial differences) or the speed/acceleration/jerk with which individuals reach these expressions (i.e., kinematic differences). Further research is necessary to a) characterise the expressive differences between autistic and non-autistic individuals, b) ascertain whether there are greater expressive differences between the groups for angry compared to happy and sad expressions and, c) confirm whether such differences in movement profile contribute to emotion recognition difficulties.

Another potential explanation for why autistic individuals have specific difficulties recognising anger concerns facial information sampling. Autistic individuals are thought to exhibit a local, rather than global, processing style[165-168], wherein they focus on specific regions of the face such as the mouth[224-226]. Given that the majority of expressive information for anger is thought to be conveyed around the eyes[227,228], the autistic participants may struggle to recognise this emotional facial expression. Conversely, these individuals may *not* struggle to recognise happiness and sadness because, for these emotions, the mouth contains relatively more expressive information[101]. As such, a local-processing style characterised by a focus on the mouth region may only impede the recognition of anger, and not happiness or sadness, for autistic individuals. Further research which employs eye tracking is necessary to determine whether differences in facial information sampling underpin selective difficulties recognising anger.

There is growing support for the alexithymia hypothesis, not only with respect to facial emotion recognition (e.g., [209,212,213,335]), but also with vocal and musical emotion recognition[357,358], and in related domains such as empathy[208]. As these literatures grow, establishing what can and cannot be explained by the alexithymia hypothesis is of increasing importance not only to academics working in the field but also to clinicians for whom it is important to understand which aspects of behaviour and cognition are indicative of autism, and which are more representative of alexithymia. In the present study, we found that self-reported alexithymia was not predictive of the effect of spatial or kinematic manipulation on emotion recognition from motion cues, emotion recognition accuracy in general, or emotion recognition accuracy specifically relating to angry videos at the normal spatial and speed level. However, when we decomposed our accuracy measure into the magnitude of ratings for the correct and incorrect emotions, we found that elevated alexithymia was associated with increased ratings for both correct and incorrect emotions. Consequently, these data suggest that, in the context of our task, individuals with high levels of alexithymic traits can recognise emotion from motion cues to the extent that they can, for example, rate an angry PLF as *more* angry, relative to happy and sad. However, compared to individuals low in alexithymic traits, they are more likely to rate a PLF high for *all* emotion categories.

One possible explanation for the absence of a significant relationship between alexithymia and emotion recognition accuracy in our study is linked to the use of degraded facial motion stimuli. Bird, Press and Richardson[359] demonstrated that impairments in emotion recognition in highly alexithymic individuals may be driven by an avoidance of the eye region. It is possible that, by using degraded stimuli in which the eye-region is represented by the kinematics and spatial configuration of only 6 landmarks (white dots), we have changed the way in which attention is allocated across the face. We know, from previous work, that the speed of movement of our eye-region landmarks carries emotion-differentiating signal[239]. However, it is possible that when eyes are represented as six white dots, they are no longer avoided by highly alexithymic individuals. Thus, alexithymic individuals might process information from the eye-region of our PLF stimuli more than they would with, for example, photographic stimuli. It is also conceivable that our PLF stimuli encourage (all) observers' attention towards the mouth over the eye region. If this were the case, a correlation between alexithymia and impaired emotion recognition may be hidden since there is no known link between alexithymia and impaired recognition of emotion from mouth-region cues.

Perhaps of most interest for the field of alexithymia research is our finding that alexithymic traits are predictive of increased magnitude of *both* correct and incorrect emotion ratings. Such results are reminiscent of a literature which concerns increased emotional reactivity in alexithymic individuals[360]. However, whilst it is tempting to speculate that our results are indicative of *over*-attribution of emotion in highly alexithymic individuals, it should be noted that there is no objective ground-truth with respect to the magnitude of ratings of our PLF stimuli. Our stimuli were designed to discretely represent happy, angry and sad emotions thus one may argue that the "ground-truth" for an angry PLF, for example, is that happy and sad ratings should be zero. However, we cannot guarantee that our PLF actors did not inadvertently produce mixed emotional expressions. A broader point here is that, given the paucity of research concerning emotion-related facial motion cues, the extent to which facial movements overlap between happy, angry and sad expressions is currently unclear. Thus, whilst it may be that highly alexithymic individuals are *over-attributing* emotion, an alternative possibility is that they are more finely tuned to emotion-related motion cues and are in fact correctly identifying that some motion cues are linked to happy, sad and angry states (though perhaps with different probabilities). To resolve this interpretational issue, further research is required to establish the extent of overlap between dynamic happy, angry and sad expressions.

Limitations

In the present study, we aimed to produce statistically rigorous and replicable results. The standard alpha level ($p < .05$) has recently been called into question for its utility and appropriateness in psychological research[361-364]. Hence, we are reassured to see that our main findings remain significant, after Bonferroni-correction and, when we set a more conservative alpha threshold of 0.025. Importantly, substantial effect sizes and Bayes factors support our low p values, thus providing us with further confidence in our results. Therefore, we believe our findings make sound contributions to the literatures regarding alexithymia, ASD and dynamic facial expression recognition, however, there are several limitations to consider.

One potential limitation of this study concerns the way in which emotion recognition performance has been calculated. By using intensity ratings to calculate emotion recognition accuracy, we are unable to delineate whether individuals score poorly (1) due to difficulties distinguishing whether expressions appear angry, happy or sad, or (2) due to them perceiving the expressions to be less intensely emotional. To illustrate this, consider the following scenario. Participant A believes that a happy PLF comprises a subtle, but clear, representation of happiness, thus resulting in the attribution of a low happiness rating (e.g., two out of ten), and a rating of zero for both anger and sadness. Participant A would only score two points despite accurately discriminating that the expression is happiness and not anger or sadness. Now consider Participant B, who believes that the same happy PLF comprises a more intense version of the expression, thus resulting in a moderate happiness rating (e.g., five out of ten), and a rating of zero for both anger and sadness. Participant B would score three points higher than Participant A, however it could be argued that they are no more accurate. Rather, this latter individual just perceives the expression to be more intensely emotional. To mitigate this limitation, we also calculated binary accuracy scores, wherein participants scored one point when they attributed the highest intensity rating to the correct emotion, and zero points when they attributed the highest intensity rating to an incorrect emotion. Using these binary scores, both Participant A and Participant B would score one point for their accurate response. After calculating these scores, we conducted our analyses again (see Appendix 1.3), finding a highly similar pattern of results. Most notably, the autistic participants correctly recognised a lower proportion of angry expressions with normal spatial exaggeration and speed than their non-autistic counterparts, thus replicating our primary results. Together, these results provide convincing evidence that the autistic participants have difficulties recognising angry facial motion at the normal level, irrespective of the way in which emotion recognition accuracy is calculated.

Another potential limitation is that due to COVID-19-related restrictions on face-to-face testing, only 22 of our ASD group completed ADOS-2 assessments. As a result, we have limited information about whether the remaining 9 participants would surpass the threshold for an autism or autism spectrum diagnosis on the ADOS-2. In addition, of the 22 participants that did complete the observational assessment, just 16 met criteria for a diagnosis. Hence, it is possible that our ASD group display less frequent or lower intensity autistic behaviours than would typically be seen in an ASD population. In spite of this we identified a significant group difference. Note that this limitation may have resulted in false negatives or an underestimation of the true effect size. However, it is highly unlikely that it could have resulted in false positives or inflated effects sizes.

Another potential limitation of this study is that we used the self-report TAS-20 to measure alexithymia. Whilst 89% of studies comparing the emotional self-awareness of autistic and non-autistic participants use self-report measures (and 62% use the TAS-20[149]), some authors (e.g., [365,366]) have questioned their utility as "people with alexithymia, by definition, should not be able to report their psychological state"[366]. However, endeavours to develop objective measures of alexithymia are in their infancy and early attempts are yet to be replicated (e.g., [367,368]) and thus self-report measures are necessary. Whilst the TAS-20 has long been the gold-standard tool for assessing alexithymia, there are some concerns that it might actually be a measure of psychopathology symptoms or current levels of psychological distress (see [365,366,369-372]. Further studies may try to replicate our results using alternative measures of alexithymia such as the Perth Alexithymia Questionnaire[373] or Bermond Vorst Alexithymia Questionnaire (BVAQ)[374], which have been argued to index an alexithymia construct that is distinct from individuals' current level of psychological distress[371]. However, since our aim was to investigate whether the alexithymia hypothesis applies, not only to emotion recognition from static face stimuli, but also to recognition from dynamic stimuli, it was crucial for the design of the current study that we employ the same measure of alexithymia (i.e., the TAS-20) as has previously been employed in the emotion recognition literature (e.g., [209,212,213,335]).

The results of the current study are informative with respect to the recognition of emotion from facial motion cues. However, given that surface properties[375], such as pigmentation/colouring[376] and shading/depth[377], are implicated in the recognition of emotion, one should be cautious about assuming that our findings generalise to full dynamic emotional expressions (e.g., video stimuli). Future research should aim to clarify whether our findings are specific to the recognition of emotion from facial motion cues, or if they are applicable more broadly to emotion recognition from full dynamic displays.

Conclusions

The current study tested whether autistic, relative to alexithymia-matched controls, have greater difficulty recognising emotions from facial motion cues. In conflict with our hypotheses, we observed that autistic, relative to control, adults showed reduced recognition of angry facial motion at the normal (100%) spatial and speed level. Interestingly, whilst for controls recognition accuracy improved across all levels of the kinematic manipulation for angry videos, autistic participants only benefitted from the 100% to 150% speed increase. Alexithymic traits were associated with elevated correct and elevated incorrect emotion ratings, but not accuracy. Our results draw attention to anger specific differences in emotion recognition between autistic and non-autistic individuals. Future research should aim to elucidate why autistic individuals exhibit differences that are specific to angry expressions.

Chapter 3: Comparing internal representations of facial expression kinematics between autistic and non-autistic adults

In the previous chapter, we discovered that the autistic participants had higher kinematic identification thresholds for anger, but not happiness or sadness, than their non-autistic counterparts. That is, the autistic participants required angry (but not happy or sad) expressions to be higher in intensity – here, in terms of speed – before the expressions could be correctly identified. As discussed in Chapter 2, these results raise the possibility that autistic individuals possess more exaggerated, higher speed, visual representations of anger than their non-autistic peers. To formally test this possibility, in the following chapter, we employed the method of adjustment to index and then compare the angry, happy and sad visual representations of autistic and non-autistic individuals with respect to speed.

Publication 2:

Comparing internal representations of facial expression kinematics between autistic and non-autistic adults

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(Published in *Autism Research*)

Reference: Keating CT, Sowden S, Cook JL. Comparing internal representations of facial expression kinematics between autistic and non-autistic adults. Autism Research. 2022 Mar;15(3):493-506. https://doi.org/10.1002/aur.2642

Abstract

Recent developments suggest that autistic individuals require dynamic angry expressions to have a higher speed in order for them to be successfully identified. Therefore, it is plausible that autistic individuals do not have a 'deficit' in angry expression recognition, but rather their internal representation of these expressions is characterised by very high-speed movement. In this study, matched groups of autistic and non-autistic adults completed a novel emotion-based task which employed dynamic displays of happy, angry and sad point light facial (PLF) expressions. On each trial, participants moved a slider to manipulate the speed of a PLF stimulus until it moved at a speed that, in their 'mind's eye', was typical of happy, angry or sad expressions. Participants were shown three different types of PLFs – those showing the full-face, only the eye region, and only the mouth region, wherein the latter two were included to test whether differences in facial information sampling underpinned any dissimilarities in speed attributions. Across both groups, participants attributed the highest speeds to angry, then happy, then sad, facial motion. Participants increased the speed of angry and happy expressions by 41% and 27% respectively and decreased the speed of sad expressions by 18%. This suggests that participants have 'caricatured' internal representations of emotion, wherein emotion-related kinematic cues are over-emphasised. There were no differences between autistic and non-autistic individuals in the speeds attributed to full-face and partial-face angry, happy and sad expressions respectively. Consequently, we find no evidence that autistic adults possess atypically fast internal representations of anger.

3.1. Introduction

Autism spectrum disorder (ASD) is a neurodevelopmental disorder, characterised by difficulties in social communication, and restricted and repetitive interests[151]. The question of whether autistic individuals exhibit atypical facial emotion recognition has been debated for over 30 years (see [146,216,217] for reviews). However, to date this literature has largely focused on the recognition of emotion from *static* face stimuli. This bias in the literature potentially reflects a broader bias across the entirety of the emotion perception literature. Indeed, it is well established that the spatial features of facial expressions (i.e., the configuration of facial features relative to one another) are important for emotion recognition and thus that emotion can be recognised from static snapshots of faces[378-381]. In contrast, a limited number of studies have investigated the influence of *dynamic* (changing over time) emotion cues such as the *temporal* order of face actions within a sequence (see [80,382-384]), and facial movement *kinematics*, where kinematic information concerns all properties of movement except force and in the context of facial movement typically refers to speed, acceleration, and jerk (change in acceleration)[239].

Recent developments in the facial emotion literature have started to tip this balance (e.g., [80,239,382-384]). Consequently, dynamic information is increasingly considered a valuable source of cues with respect to emotion recognition. For instance, in a series of experiments with non-autistic participants, Sowden et al[239] demonstrated that facial movement kinematics (in this instance, speed) comprise important cues for emotion recognition. More specifically, these authors showed that across different facial actions (i.e., eyebrow widening, nose lengthening, lip raising, mouth widening and mouth opening) and emotional expression contexts (i.e., posed, spontaneous and communicative), happy and angry expressions were typically fastest, and sad expressions were slowest[239]. Importantly, Sowden et al[239] also demonstrated that kinematic cues play a causal role in facial emotion judgements. Their paradigm employed point-light displays (a series of dots that convey biological motion) of the face (point light faces; PLFs) that had been manipulated to achieve three spatial levels, ranging from reduced to increased spatial movement (50% spatial; 100%; 150%), and three kinematic levels, ranging from reduced to increased speed (50% speed; 100%; 150%). Sowden et al[239] demonstrated that speeding-up facial expressions promoted anger and happiness judgements and slowing-down expressions encouraged sadness judgments, thus the speed of movement of internal facial features influences observers' judgements of emotion.

In order to redress the bias towards the use of static stimuli in the ASD emotion recognition literature, our most recent work employed the paradigm developed by Sowden and colleagues to investigate emotion recognition from facial motion cues in ASD[385]. There were two key findings from our recent study. Firstly, autistic adults (relative to non-autistic controls who were matched on age, gender, non-verbal reasoning and alexithymia) had significantly lower emotion recognition accuracy for angry, but not happy or sad, facial motion when PLFs were unmanipulated (i.e., when they were played at their normal (100%) speed and with normal (100%) degree of spatial movement across frames)[385]. Secondly, whilst for controls, recognition accuracy increased when angry facial motion was sped up from 50% to 100% speed and from 100% to 150% speed, the recognition accuracy of autistic participants only increased from 100% to 150% (and not from 50% to 100%)[385]. Note that since our groups were matched in terms of alexithymia (a subclinical condition, characterised by difficulties identifying and expressing emotions[194]) differences between our groups were related to autistic, not alexithymic, characteristics (for further discussion of this issue see [207,209]). In sum, we observed that autistic adults exhibited typical anger recognition for high speed (150%) PLFs, but reduced accuracy (relative to non-autistic adults) at a lower speed (100%).

Our recent findings therefore illustrate differences between autistic and non-autistic adults in emotion recognition from facial *kinematic* information[385]. However, these differences are specifically restricted to anger and do not extend to happiness and sadness[385]. Interestingly, this anger-specific difficulty is also mirrored in the static emotion recognition literature. A number of empirical studies indicate that the recognition of anger is particularly challenging for autistic individuals[219-222]. Indeed, a meta-analysis of this literature suggests that there are greater differences between autistic and non-autistic individuals in the recognition of angry than there are for happy and sad expressions[191]. Further to this, Song and Hakoda demonstrated that autistic children (relative to non-autistic children) require angry, but not happy or sad, expressions to have higher emotional intensity in order for them to be correctly identified[222]. More specifically, to estimate 'identification thresholds' (the intensity at which an expression is identified correctly on two consecutive trials) Song and Hakoda used static photographic stimuli at varying expressive intensities (constructed by repeatedly morphing a full expression with a neutral expression to result in 9 intensity levels for each emotion) and asked participants to select which emotion most effectively described the emotion shown (out of six possible options)[222]. They found that, compared to non-autistic counterparts, autistic children had significantly higher identification thresholds for angry expressions, meaning that a higher intensity was necessary before an expression could be reliably identified as angry. Importantly, there were no significant differences between the groups for identification thresholds for happiness or sadness[222]. These findings suggest that autistic individuals require a higher intensity of emotion before a *static* facial expression can be reliably identified as angry. At present there is no equivalent study for *dynamic* facial expressions.

Our recent results[385] raise the hypothesis that autistic adults may require a higher intensity of emotion before a *dynamic* facial expression can be reliably identified as angry. That is, our results clearly illustrated that autistic adults did not have a categorical 'deficit' in the recognition of anger[385]. Rather, relative to controls, autistic participants required a higher speed before they could accurately identify angry expressions[385]. It is therefore plausible that autistic adults do not have a 'deficit' in the recognition of angry expressions, but rather their internal representation of angry facial expressions (i.e., the speeds at which they would visualise these emotions in their "mind's eye") is characterised by very high-speed movements[385].

Atypical internal representations of facial expressions could influence the accuracy of emotion recognition via multiple potential mechanistic pathways. For example, according to "template matching" models of emotion labelling (see [147,386]), when trying to interpret an expression, one compares the physical features of the observed expression to one's own internal representations or expression "templates" and "reads off" the corresponding emotion label[147]. Consequently, correct labelling of the observed expression is more likely if the "sender" and "receiver" have matching internal representations of emotions (see [147,387]). Thus, individuals with internal representations of emotion that are very common within the general population are more likely, on average, to correctly label observed expressions. Whereas correct emotion labelling may be reduced in individuals with uncommon internal representations. In this case, an abnormally high-speed representation of anger may lead to reduced accuracy in recognising "normal speed" angry stimuli because only high-speed angry expressions match the observer's internal representation of anger. In addition, internal representations of facial expressions provide predictive information based on previous experience (i.e., 'priors')[80,388,389]. Consequently, an abnormally high-speed representation of anger may lead to reduced accuracy in recognising "normal speed" angry stimuli by acting as an atypical prior which biases subsequent perception of incoming face stimuli[260].

The question of why differences in autistic facial emotion recognition are specific to anger is a difficult one. If autistic individuals have internal representations of anger that are characterised by atypically high-speed movement, why would this be selective to anger, why is this not also the case for emotions such as happiness? One potential explanation relates to differences in facial information sampling. There is evidence to suggest that autistic individuals tend to avoid looking at the eye region of the face, and instead preferentially look at the mouth region[224-226] (though also see [359] for a debate concerning the role of alexithymia in explaining differences in autistic facial information sampling). Some researchers believe that this is a strategy that autistic individuals adopt to modulate amygdala activation[390-392], which is often atypical in ASD in response to faces[229, 393-399], as the amygdala is highly responsive to the eye region of emotional facial expressions[400]. Given that for anger the majority of expressive information is thought to be conveyed in the upper half of the face, around the eye region[227,228], autistic participants may require greater "signal" (i.e., faster movement) when recognising anger because they are focusing on an information-poor part of the face (i.e., the mouth). This would not be the case for happy and sad because, for these emotions, the mouth comprises a more information rich part of the face[379,401].

To investigate whether, compared to non-autistic adults, autistic adults have different internal representations of anger that are characterised by higher mean speed, the current study employed a novel emotion-based task which we refer to as the "PLF slider task". Using a method of adjustment design, participants were required to manipulate a sliding scale in order to speed-up or slow-down PLF stimuli until the stimuli matched their internal representation of anger, happiness and sadness. PLF stimuli were employed to facilitate comparisons between the current study and our previous study[385], to draw participants' attention to facial motion cues as opposed to static cues such as texture, luminance, and contrast, and because the use of point lights to represent particular facial landmarks simplifies the task of modulating facial speed in real time. This method estimates, for each participant, an index of mean percentage speed attribution. We hypothesised that, relative to control participants, autistic adults would attribute higher mean speeds to angry, but not happy or sad, stimuli. Furthermore, we reasoned that, if higher speed thresholds for anger, are driven by a focus on the mouth region – an information-poor part of the face with respect to anger recognition – differences between the ASD and control groups should disappear if participants are required to focus on information-rich parts of the face (i.e., the eye region). To test this hypothesis, we included a partial face condition, in which participants saw only the upper or lower face of the face on each trial.

3.2. Method

See https://osf.io/sgxum for the pre-registration relating to this report.

3.2.1. Participants

A total of 25 autistic and 25 non-autistic participants were recruited from a local database held by the Birmingham Psychology Autism Research Team and Prolific. The study was approved by the Science, Technology, Engineering and Mathematics (STEM) ethics committee at the University of Birmingham (ERN_16-0281AP9B) and was conducted in accordance with the principles of the revised Helsinki Declaration.

The pre-registered sample size was based on an *a priori* power analysis conducted using G*Power[402], which focuses on replicating the group-difference[385] in recognition accuracy (between ASD and control individuals) for angry videos at the normal spatial and speed level. Using data from our previous study[385], 25 participants are required in each group in order to have 80% power to detect an effect size of 0.719 (Cohen's d) at alpha level 0.05 for this group-difference in accuracy.

All participants in the ASD group had previously received a clinical diagnosis of ASD from an independent clinician. The level of autistic traits of 21 individuals in the ASD group was assessed using the Autism Diagnostic Observation Schedule (version 2)[345]. Of those who did complete the ADOS assessment, 16 met criteria for ASD (5 autism, 11 autism spectrum; mean ADOS-2 score = 9.62). Although, five individuals in the ASD group did not meet criteria for diagnosis according to the ADOS, they had previously received a clinical diagnosis of ASD and thus still participated in the study. Unfortunately, it was not possible to complete observational assessments on four ASD participants due to restrictions on face-to-face testing during the COVID-19 pandemic. The participants in the ASD group had significantly higher Autism Quotient scores[304] than those in the non-autistic group (see Table 3.1).

3.2.2. Procedures

Participants completed our group-matching measures followed by the PLF slider task, which were both administered online via Qualtrics and Gorilla.sc.

Group-matching measures

To facilitate group-matching, participants provided information concerning their age and gender, and completed the Toronto Alexithymia Scale (TAS-20)[344] and the Matrix Reasoning Item Bank (MaRs-IB)[343], an 8-minute assessment of non-verbal reasoning ability. The Autism Quotient (AQ)[304] was also completed to ensure that the autistic group were significantly higher in autistic traits. All of these measures were completed online.

PLF slider task

The PLF slider task is a novel tool for the estimation of the mean speed of a participant's internal representation of emotional expressions. In this task, on each trial, participants are presented with a PLF stimulus video (on average, approximately 6 seconds in length) which was looped such that when the stimulus reached the end it played again from the beginning.

Participants were instructed to "move the slider to change the speed of this video until it matches the speed of a typical ANGRY/HAPPY/SAD expression" (note that participants were only asked to change the speed of the expression to match the emotion that was displayed in the stimulus video, i.e., on a trial where an angry facial expression was presented, participants were only asked to manipulate the speed of the video so that it matched the speed of a typical angry expression). Consequently, participants were matching the speed of the displayed PLF to their internal representation of that expression. Participants could change the speed of the video by moving a slider to the left (decrease speed) or right (increase speed) on a visual analogue scale ranging from 25% to 200% of the recorded speed. Once participants were satisfied that the speed of the video matched that of a typical angry/happy/sad expression, they could press the spacebar to continue. There was no time limit for participants to respond on each trial. This task indexes the percentage speed attributed, by participants, to each of the PLF stimulus videos (e.g., 125% speed).

The PLF stimulus videos (taken from Sowden et al[239]) were originally created by taking video recordings of four actors (two male, two female) verbalising sentences whilst posing the three target emotions (angry, happy and sad). These recordings were then fed into OpenFace[403] from which the x and y coordinates of 68 facial landmarks were extracted at 25 frames per second (FPS). To create the PLF stimuli, Sowden and colleagues[293] displayed successive frames of these coordinates as white dots on a black background (using Cogent graphics for MATLAB) and saved these displays as video files. This resulted in four videos per emotion (i.e., one for each actor).

There were two main sections of the PLF slider task. In the first part of the task (the full-face condition), participants were shown full PLF stimuli made up of 68 white dots on a black background (see Appendix 2.1). In the second part of the task (partial face condition), participants were shown partial PLF stimuli comprising 32 dots on a black background displaying either the eye or mouth region (see Appendix 2.1). In the first part of this task (the full condition), participants were shown four repetitions of *full-face* PLF stimuli for each of the four actors, however, each repetition had a different starting speed (80%, 90%, 100% and 110% speed). The starting speed manipulation ensured that the point on the scale relating to the normal recorded (100%) speed was not always in the same spatial location. This resulted in 16 *full-face* videos per emotion (4 actors x 4 starting speeds x 3 emotions = 48 trials in total). Participants completed three practice trials (one for each emotion at 100% starting speed) and then the 48 randomly ordered experimental trials across three blocks. In the second part of the task (the partial face condition), participants were shown two repetitions of eye PLF stimuli, and two repetitions of mouth PLF stimuli, for each actor. The starting speeds for these repetitions were 80% and 100% speed respectively. This resulted in 8 eye and 8 mouth PLF stimulus videos per emotion. Participants completed 48 randomly ordered experimental trials (4 actors x 2 face areas x 2 starting speeds x 3 emotions = 48 trials in total) across three blocks.

3.2.3. Score Calculations

Group-matching measures

Scores on the AQ and TAS-20 were calculated as a sum of participants' responses whereby, in line with published standards for each questionnaire, some questions were reverse scored. Higher scores on the AQ (maximum score: 50) and TA-20S (maximum score: 100) reflect higher levels of autistic and alexithymic traits respectively. Scores on the Matrix Reasoning Item Bank (NVR) were calculated as the percentage of correct responses within 8 minutes.

PLF slider task

Before calculating percentage speed change and attributed speed (see below), we adjusted for the PLF starting speed. To do so, we multiplied the percentage speed attributed to the videos moving at 80% speed by 0.8, 90% speed by 0.9, and 110% speed by 1.1 (if a participant attributed 125% speed to a video with 80% starting speed, they actually attributed 100% speed to the video; 125 x 0.8 = 100; that is, they adjusted the speed of the video such that it played back at 100% of the speed at which it was recorded). This gave us 'adjusted percentage speed attributions'.

Percentage speed change. In order to index whether participants' internal representations of emotion were faster or slower than the 100% (natural) speed of the stimulus videos, we calculated percentage speed change. This index was calculated by subtracting 100 from all of the adjusted percentage speed attributions made by participants (e.g., if a participant attributed 73% speed to a video (after adjusting for starting speed), the percentage speed change would be -27%). Therefore, this index of percentage speed change reflects how much participants changed the speed of the PLF stimulus video relative to the speed it was recorded at (since we had already corrected for starting speed).

Attributed speed. In order to answer the question of whether autistic and non-autistic individuals have differing internal representations of angry, happy and sad dynamic facial motion in terms of speed, we needed to calculate the speed (in pixels per frame) that participants attributed to each of these emotions. We did this via three steps; (1) calculating the recorded speed in pixels per frame for each PLF stimulus; (2) calculating an attribution multiplier based on the participants' responses (i.e., based on percentage speed change) and finally (3) calculating attributed speed by multiplying the recorded speed of the PLFs with this attribution multiplier.

For step one, we followed procedures outlined in Sowden et al. (2021). The 12 different PLF videos (4 actors x 3 emotions) were fed into the open-source software OpenFace[403] to identify the x and y coordinates (in pixels) of 68 facial landmarks, sampled at a rate of 25Hz. Subsequently, key points (e.g., inner eyebrow) were identified and distances between these key points were calculated as the square root of the sum of squared differentials of the x and y co-ordinates of each key point. Next, these face distances were summed to create five face "actions" (as in [239,277]) including inner eyebrow widening, nose lengthening, lip raising, mouth widening and mouth opening. Speed was calculated as the absolute value of the average change in distance between relevant points on the face for each face action across the whole video clip, and thus represents the absolute mean speed (pixels/frame) for each facial action, within the whole recording window. These speed vectors were low pass filtered at 10 Hz to include human movement signal and exclude noise associated with the MATLAB diff function. Since our speed measure concerns the movement of face actions (such as eyebrow widening) it represents the speed of movement of the internal features of the face, not the speed of rigid-body head movement. We focus on the internal features because we know that their movement speed is important in emotion recognition[239]. For the full-face videos, we calculated mean speed by taking an average for each video across all 5 facial actions. For videos in the partial face condition, we took an average of speed across the relevant facial action regions (e.g., averaging across eyebrow widening and nose lengthening for PLFs displaying the eyes, and averaging across lip raising, mouth widening and mouth opening for PLFs displaying the mouth).

Next, we transformed participants' responses to each of the full-face and partial face emotional videos into "attribution multipliers" by dividing percentage speed change by 100 and then adding 1 to all the values (e.g., for a trial in which a participant has increased the speed of a video relative to the speed at which it was recorded by 40%, the attribution multiplier would be 1.4. For a trial in which a participant decreases the speed by 27%, the attribution multiplier would be 0.73). Following this, we calculated attributed speed by multiplying the "attribution multiplier" by the mean speeds that we calculated (see above) for each of the full-face/partial-face emotional videos. Finally, we calculated the mean speeds attributed to the angry, happy and sad videos by taking an average across the videos for each emotion respectively.

3.2.4. Statistical Analyses

Preregistration, data, and analysis files are available online at https://osf.io/xa23h/. For all analyses, we used a p = .05 significance threshold to determine whether to accept or reject the null hypothesis. The frequentist approach was also supplemented with the calculation of Bayes Factors, which quantify the relative evidence for one theory or model over another. For all Bayesian analyses, we followed the classification scheme used in JASP[352]: BF_{10} values between one and three represent weak evidence, between three and ten moderate evidence, and greater than ten strong evidence, for the experimental hypothesis. Similarly, BF_{10} values between 1 and $\frac{1}{3}$ reflect weak evidence, between $\frac{1}{3}$ and $\frac{1}{10}$ moderate evidence, and smaller than $\frac{1}{10}$ strong evidence, for the null hypothesis respectively[352]. For all Bayesian ANOVAs, a default Uniform prior was used. For all Bayesian independent samples t-tests, a default prior was used (Cauchy width = 0.707).

PLF slider task

To test our first hypothesis, we conducted two mixed 2 x 3 Analysis of Variance (ANOVA), with the between-subjects factor *group* (ASD, control) and the within-subjects factor *emotion* (angry, happy, sad). In the first of these ANOVAs, we used percentage speed change as our dependent variable (DV), and in the second we used mean attributed speed as our DV. To test our second hypothesis, we conducted two mixed 2 x 2 x 3 ANOVAs with the between-subjects factor *group* (ASD, control), and the within-subjects factors *face area* (eyes, mouth) and *emotion* (angry, happy, sad). As before, in the first of these ANOVAs, we used percentage speed change as our DV, and in the second we used mean attributed speed.

3.3. Results

3.3.1. Group Demographics

Participants were matched on age, gender, NVR and alexithymia. The ASD group were significantly higher in autistic traits. In order to ensure that there were no outliers in survey scores, we verified that each of the participants' scores on the AQ, TAS-20 and MaRs-IB were no more than three standard deviations away from their group mean. Descriptive statistics for these groups, in addition to the statistics pertaining to group comparisons are presented in Table 3.1. Information about participants' ethnicities is reported in Appendix 2.2.

Table 3.1.

Means, standard deviations and group differences of participant characteristics. In the central columns, means are followed by standard deviations in parentheses.

	Control (n=25)	ASD (n=25)	Significance
Gender	9 Female, 15 Male, 1 Other	11 Female, 13 Male, 1 Other	p = .842
Age	27.57 (9.70)	31.98(9.88)	p = .118
NVR	63. 31(15.75)	55.59(17.81)	p = .111
TAS-20	56.00(12.97)	57.96(12.03)	p = .582
AQ	20.04(7.17)	34.60(9.40)	p < .001

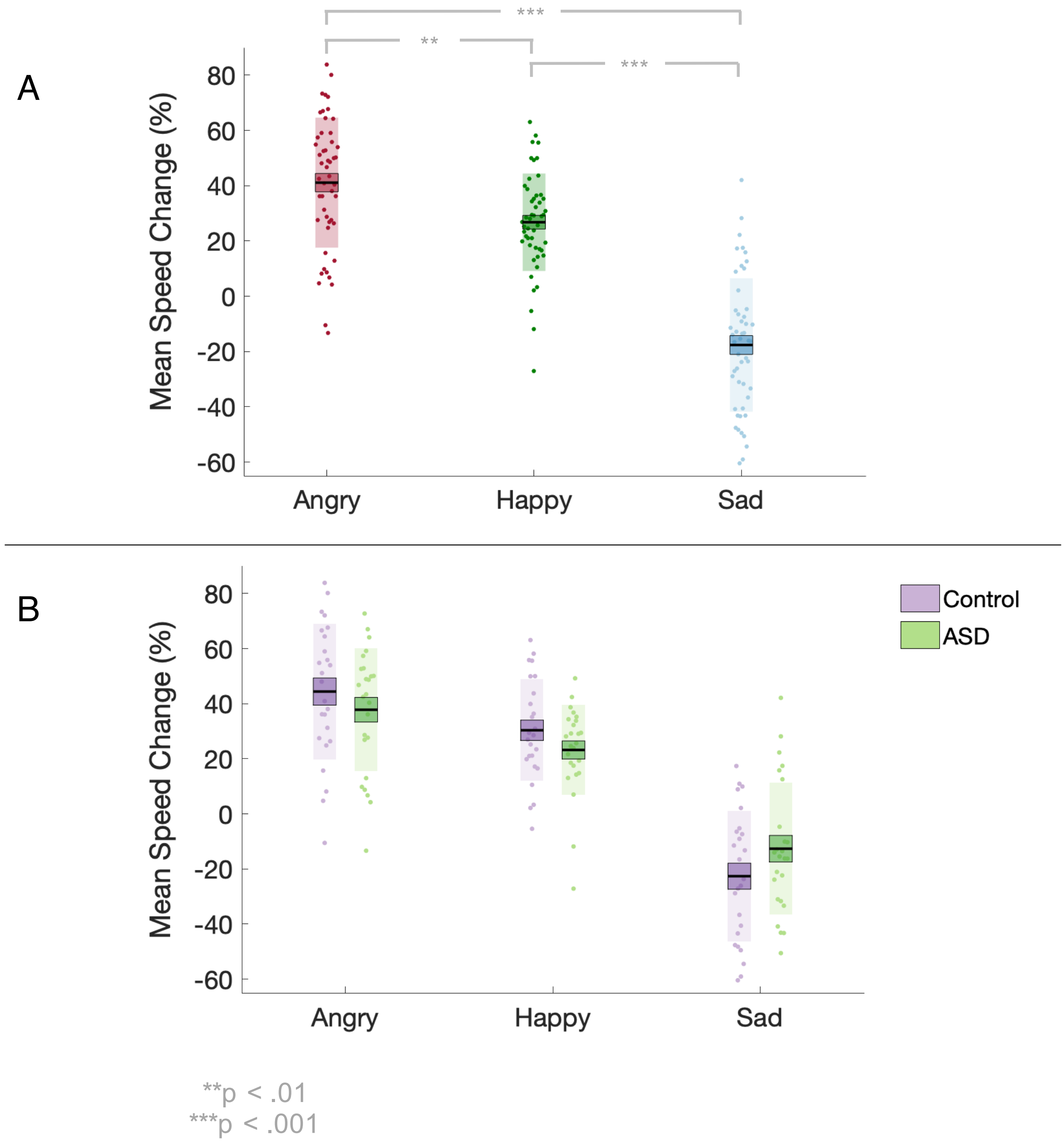
Note. Non-verbal reasoning (NVR), Toronto Alexithymia Scale (TAS-20), Autism Quotient (AQ). Age is in years.

3.3.2. Percentage Speed Change Analyses

In order to compare the extent to which autistic and non-autistic individuals increased/decreased speed of emotional expression PLFs, we conducted a mixed 2 x 3 ANOVA with the between-subjects factor *group* (ASD, control) and the within-subjects factor *emotion* (angry, happy, sad), and with percentage speed change as the dependent variable (DV). This analysis revealed a main effect of *emotion* [$F(2,96) = 84.78$, $p < .001$, $\eta_P^2 = .64$, $BF_{10} = 2.58e^{25}$; Figure 3.1], with participants speeding up angry expressions the most [mean(standard error of the mean (SEM)) = +41.10% (3.33)], followed by happy expressions [mean(SEM) = +26.78% (2,47)], and slowing down sad expressions [mean(SEM) = -17.64% (3.37)]. Importantly, we identified no main effect of *group* [$t(48) = 0.67$, $p = .669$, mean difference = 1.26%, $BF_{10} = 0.20$] and, contrary to our hypothesis, no *emotion x group* interaction [$F(2,96) = 2.14$, $p = .135$, $\eta_P^2 = .04$, $BF_{10} = 0.90$; Figure 3.1]. Since our BF_{10} value only provided weak evidence to support the null hypothesis, we proceeded to unpack this interaction. This showed that there were no significant differences between the groups in the percentage speed change (even before Bonferroni-correction) for angry [$t(48) = 0.99$, $p = .326$, mean difference = 6.60%, $BF_{10} = 0.42$], happy [$t(48) = 1.45$, $p = .154$, mean difference = 7.15%, $BF_{10} = 0.67$] or sad [$t(48) = -1.48$, $p = .145$, mean difference = -9.99%, $BF_{10} = 0.69$] facial motion. Notably, in conflict with our hypothesis, percentage speed change for anger was numerically higher in the non-autistic relative to autistic participants [non-autistic mean(SEM) = +44.40%(4.70%); autistic mean(SEM) = +37.79%(4.70%)].

Figure 3.1.

Mean percentage speed change attributed to each target emotion for all participants (A) and for control and autistic participants respectively (B).

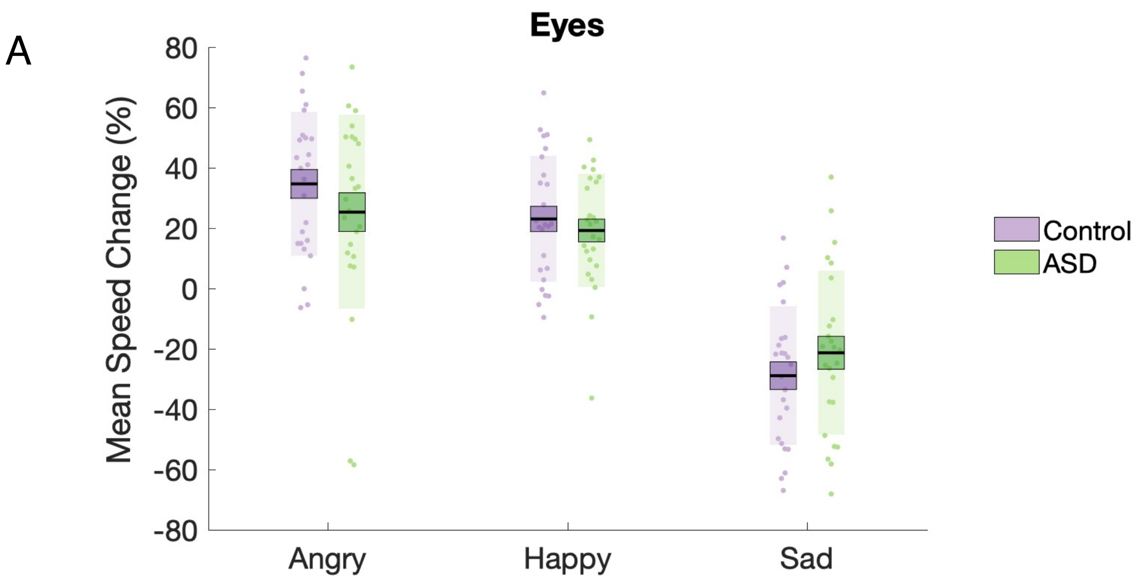


Note. In both graphs, the black line represents the mean, the shaded region represents one standard deviation. The coloured box represents one standard error around the mean and the dots represent individual datapoints.

In the following additional analyses, the dependent variable (percentage speed change) is calculated only from the trials in the partial face condition. To analyse this data, we conducted a mixed 2 x 2 x 3 ANOVA with the between-subjects factor *group* (ASD, control), and the within-subjects factors *face area* (eyes, mouth) and *emotion* (angry, happy, sad) in order to compare the percentage speed change for the eye and mouth regions of the emotional expressions across groups. Once again we identified a main effect of *emotion* [$F(2,96) = 75.464$, $p < .001$, $\eta_P^2 = .61$, $BF_{10} = 2.65e^{46}$], with participants speeding up the eye and mouth regions most for angry [mean(SEM) = +31.84% (3.61)], followed by happy expressions [mean(SEM) = +20.97% (2.54)], and slowing down these regions for sad expressions[mean(SEM) = -23.77% (3.61)]. In addition, this analysis found no main effect of *group* [$t(48) = 0.56$, $p = .575$, mean difference = 2.01%, $BF_{10} = 0.17$], or *face area* [$F(1,48) = 3.75$, $p = .059$, $\eta_P^2 = .07$, $BF_{10} = 0.14$], no *face area x group* interaction [$F(1,48) = 0.02$, $p =.900$, $\eta_P^2 = .00$, $BF_{10} = 0.17$], or *face area x emotion interaction* [$F(2,96) = 1.34$, $p = .266$, $\eta_P^2 = .03$, $BF_{10} = 0.07$], and finally no *face area x emotion x group* interaction [$F(2,96) = 0.27$, $p = .270$, $\eta_P^2 = .01$, $BF_{10} = 0.12$]. Our analysis also revealed that the *emotion x group* interaction was not significant [$F(2,96) = 1.81$, $p = .178$, $\eta_P^2 = .04$, $BF_{10} = 2.43$] however since Bayesian statistics provide weak evidence for the presence of an emotion x group interaction, we ran post-hoc independent samples t-tests. This identified that there were no significant differences between autistic and control participants in percentage speed change (before Bonferroni-correction) for angry [$t(48) = 1.28$, $p = .205$, mean difference = 9.27%, $BF_{10} = 0.55$], happy [$t(48) = 0.99$, $p = .330$, mean difference = 5.00%, $BF_{10} = 0.42$], or sad [$t(48) = -1.14$, $p = .260$, mean difference = -8.24%, $BF_{10} = 0.48$; see Figure 3.2] displays when the eyes and mouth were grouped together (as would be the case in the emotion x group interaction). Once again, contrary to our hypothesis, percentage speed change for anger was numerically higher in non-autistic relative to autistic participants [non-autistic mean(SEM) = +36.48%(5.11%); autistic mean(SEM) = +27.21%(5.11%)].

Figure 3.2.

Mean percentage speed change attributed to each target emotion for the eyes (panel A) and mouth (panel B) for control and autistic participants.



Note. In both graphs, the black line represents the mean, the shaded region represents one standard deviation. The coloured box represents one standard error around the mean and the dots represent individual datapoints.

3.3.3. Attributed Speed Analyses

In order to compare the mean speed attributed to the emotional expressions by autistic and non-autistic individuals, we conducted a mixed 2 x 3 ANOVA with the between-subjects factor *group* (ASD, control) and the within-subjects factor *emotion* (angry, happy, sad), and with mean attributed speed as the DV. This analysis revealed a main effect of *emotion* [$F(2, 96) = 254.61$, $p < .001$, $\eta_P^2 = .84$, $BF_{10} = 5.46e^{49}$], with participants attributing the highest speeds to angry [mean(SEM) = 3.18(0.08) pixels/frame], followed by happy [mean(SEM) = 2.21(0.04) pixels/frame], and finally sad [mean(SEM) = 1.18(0.05) pixels/frame] expressions. Importantly, we identified no main effect of *group* [$t(48) = 0.721$, $p = .475$, mean difference = 0.04 pixels/frame, $BF_{10} = 0.20$] and, contrary to our hypothesis, no *emotion x group interaction* [$F(2,96) = 1.74$, $p = .189$, $\eta_P^2 = .04$, $BF_{10} = 0.60$]. Since our Bayes Factor only provided weak evidence to support the null hypothesis, we proceeded to unpack this interaction. This showed that there were no significant differences between the groups in the speeds attributed to angry [$t(48) = 0.97$, $p = .337$, mean difference = 0.15 pixels/frame, $BF_{10} = 0.42$], happy [$t(48) = 1.38$, $p = .172$, mean difference = 0.12 pixels/frame, $BF_{10} = 0.61$] or sad [$t(48) = -1.55$, $p = .128$, mean difference = -0.15 pixels/frame, $BF_{10} = 0.75$] facial motion (note that the stats shown are before Bonferroni-correction). Notably, in conflict with our hypothesis, autistic participants attributed numerically lower speeds to angry facial motion than their non-autistic counterparts [autistic mean(SEM) = 3.11 pixels/frame(0.11 pixels/frame); non-autistic mean(SEM) = 3.26 pixels/frame(0.11 pixels/frame)].

In the following additional analyses, the dependent variable is calculated only from the trials in the partial face condition. To analyse this data, we conducted a mixed 2 x 2 x 3 ANOVA with the between-subjects factor *group* (ASD, control), and the within-subjects factors *face area* (eyes, mouth) and *emotion* (angry, happy, sad) in order to compare the mean speed attributed to the eye and mouth regions of the emotional expressions across groups. Once again we identified a main effect of *emotion* [$F(2,96) = 221.54$, $p < .001$, $\eta_P^2 = .82$, $BF_{10} = 9.60e^{17}$], with participants attributing the highest speed to angry [mean(SEM) = 2.70(0.07) pixels/frame], followed by happy [mean(SEM) = 1.96(0.04) pixels/frame], and finally sad [mean(SEM) = 1.01(0.05) pixels/frame] expressions. In addition, this analysis identified a main effect of *face area* [$F(1,48) = 3732.59$, $p < .001$, $\eta_P^2 = .99$, $BF_{10} = 1.25e^{46}$], with the highest speeds attributed to the mouth region [mean(SEM) = 2.85(0.04) pixels/frame], and the slowest speeds attributed to the eye region [mean(SEM) = 0.93(0.02) pixels/frame]. We also found a significant *emotion x face area* interaction [$F(2, 96) = 262.38$, $p < .001$, $\eta_P^2 = .85$, $BF_{10} = 4.99e^{41}$], which suggested that there was a larger effect of face area for happy [$F(1,48) = 1922.89$, $p < .001$, $\eta_P^2 = .98$, $BF_{10} = 4.17e^{52}$] and angry [$F(1,48) = 1266.40$, $p < .001$, $\eta_P^2 = .96$, $BF_{10} = 7.56e^{46}$] than sad [$F(1,48) = 331.58$, $p < .001$, $\eta_P^2 = .87$, $BF_{10} = 1.42e^{23}$] facial motion. Taken together, higher speeds were attributed to the mouth than eye region across all emotions, but this difference was greater for happy and angry than sad facial motion (see Figure 3.3). There was no main effect of group [$t(48) = 0.98$, $p = .334$, mean difference = 0.06 pixels/frame, $BF_{10} = 0.16$], no *emotion x group* interaction [$F(2,96) = 1.75$, $p = .188$, $\eta_P^2 = .04$, $BF_{10} = 0.09$] or *face area x group* interaction [$F(1,48) = 1.70$, $p = .199$, $\eta_P^2 = .03$, $BF_{10} = 0.18$], and finally no *face area x emotion x group* interaction [$F(2,96) = 1.71$, $p = .196$, $\eta_P^2 = .03$, $BF_{10} = 0.24$].

Figure 3.3.

Mean attributed speed (pixels/frame) to each target emotion for the eyes (orange) and mouth (blue).

Note. For each condition, the black line represents the mean and the shaded region represents one standard deviation. The coloured box represents one standard error around the mean and the dots represent individual datapoints.

3.4. Discussion

The current study used a novel PLF slider task to investigate whether autistic and non-autistic individuals have differing internal representations of angry, happy and sad dynamic facial motion in terms of speed. In doing so, we identified that the participants, as a whole, attributed the highest speeds to angry, followed by happy, followed by sad expressions for both full-face and partial-face (eye and mouth) PLFs. More specifically, we found that on average, participants *increased* the speed of full angry expressions by 41%, *increased* the speed of full happy expressions by 27%, and finally *decreased* the speed of full sad expressions by 18%.

Our primary concern, however, was whether autistic and non-autistic individuals possess *differing* internal representations of the speeds of dynamic emotional expressions. We hypothesised that the ASD and non-autistic control group would attribute different mean speeds to full-face angry (and not happy or sad) expressions, that is we predicted an interaction between group and emotion. Our frequentist analyses showed that there was no significant group by emotion interaction in both the percentage speed change and attributed speed analyses. However, Bayesian analyses indicated that our data only provided anecdotal evidence in support of the null hypothesis (that there is *no* group x emotion interaction). To explore whether there was a trend towards a difference between the groups in the speeds attributed to angry expressions we unpacked the interaction. This revealed that there were no group differences in the speeds attributed to full-face happy, sad and, importantly, angry facial motion in both the frequentist and Bayesian analyses. Contrary to our hypothesis, for angry expressions thresholds were numerically higher for the non-autistic than for the autistic group. Thus, the evidence suggests that autistic and non-autistic individuals do not differ in their internal representations of the speed of angry facial motion.

In addition, in the partial-face condition (when participants either saw the mouth or eyes alone), our frequentist analyses identified that there was no group x emotion interaction. However, our Bayesian analyses indicated that our data provided anecdotal evidence for the presence of this interaction in the percentage speed change analysis. Importantly, unpacking this interaction demonstrated, once again, that there were no group differences in how much participants increased or decreased the speed of partial-face angry, happy and sad facial motion (in both frequentist and Bayesian analyses). Notably, in conflict with our hypothesis, percentage speed change for anger was numerically higher in the non-autistic relative to autistic participants. In addition, in our attributed speed analysis, our data provided strong evidence for the absence of a group x emotion interaction (BF_{10} = 0.09) in the partial-face condition. As such, it was apparent that when we accounted for the recorded speed of the eye and mouth expressions, the group x emotion interaction disappeared. Taken together, there were no group differences in how much participants increased or decreased the speed of partial-face angry, happy and sad facial motion, nor were there group differences in the speeds attributed to these partial-face expressions.

Our secondary concern was whether there would be significant group differences in the speeds attributed to the mouth, and not the eye, region for angry facial motion. We reasoned that if higher speed thresholds for anger were driven by a focus on the mouth region - an information-poor part of the face with respect to anger recognition - differences between the autistic and non-autistic participants should disappear if participants are required to focus on information-rich parts of the face (i.e., the eye region). Our results demonstrate that autistic and non-autistic participants attributed comparable speeds for all emotional expressions, irrespective of whether they saw information from the eye region, or mouth region alone. Indeed, our Bayesian analyses provide moderate evidence to support the null hypothesis, as shown by the Bayes Factors for the face area x emotion x group interaction in both the percentage speed change (BF_{10} = 0.12) and attributed speed (BF_{10} = 0.24) analyses. Therefore, we found no evidence to support our hypothesis that autistic and non-autistic participants would attribute different speeds for angry expressions in the mouth, but not eye, partial face condition.

One may query whether the current study would have observed significant differences between the groups if we had recruited an ASD sample that scored more highly in terms of autistic traits. We do not believe this to be the case for several reasons. Firstly, the mean AQ score in this study was comparable to that in a large-scale study with over 800 autistic participants (34.60 in the present study and 33.73 in [404]) and therefore, our sample is representative of the broader population in terms of autistic traits. Secondly, there was no correlation between autistic traits (as measured by the AQ) and mean percentage speed change [$p = .287$, $BF_{10} = 0.31$] or attributed speed [$p = .247$, $BF_{10} = 0.34$] within our sample. Therefore, even if we recruited participants who scored more highly in terms of autistic traits, it is unlikely that larger group differences would emerge. Finally, our autistic participants have comparable AQ, and ADOS scores to those in other studies (e.g., [219,385,405]) in which significant group differences in facial emotion recognition have been found.

Taken together, our results suggest that autistic and non-autistic individuals do not significantly differ in their internal representations of full and partial (eye or mouth region) angry, happy, and sad facial motion in terms of speed. Importantly, these results suggest that the finding from our previous study wherein autistic participants were less accurate (relative to alexithymia-matched non-autistic participants) in recognising angry expressions when stimuli were played at 100% of their recorded speed (but not if they were played at 150% of recorded speed), is unlikely due to differing internal representations in the speed domain. Consequently, these results force us to question other processes which may be contributing to differences in the recognition of anger in autistic samples.

One potential explanation is that whilst autistic and non-autistic individuals do not differ in their internal representations (at least in the speed domain), autistic people may be *less affected/guided* by these internal representations, and thus may exhibit differences in emotion recognition. As discussed above, template matching models of emotion recognition emphasise that, to label an expression, one must compare the incoming sensory stimulus (i.e. the facial expression) to one's internal representations of emotion and "read off" the corresponding emotion label. However, such explanations overlook the effect that prior expectations have on the perception of incoming sensory information. For example, if one expects to observe a happy expression one will attend more to features that generally signal happiness and less to features that tend to signal sadness[406]. According to Bayesian accounts, autistic people may be less affected by their priors than neurotypical people[259,260] and place greater emphasis on incoming sensory information (see [261]). Thus, for non-autistic people, expectations can bias the perception of expressions (i.e. incoming sensory stimuli) such that they better match internal representations of expected emotions. For autistic people the perception of expressions may be less affected by prior expectations. In cases where non-autistic people have informative priors (which faithfully represent statistically regularities in the environment), this process should improve emotion recognition. Thus, autistic individuals would exhibit a comparative reduction in the accuracy of emotion recognition. That is, although autistic and non-autistic people may have comparable internal representations, for non-autistic people only, expectations may bias the perception of expressions to bring them "closer" to their internal templates. For comparable emotion recognition, autistic people may require the incoming stimulus itself to be closer to their internal representation. In line with this, in our previous work[385], we observed that autistic individuals had difficulty recognising normal speed (100%) angry expressions, which are further away from the average internal representation speed (137.79%), but not those with a higher speed (150%), which are closer to the average internal representation speed for anger. Emotion recognition difficulties would be more likely for anger because, for both happy and sad expressions, there is less of discrepancy between the normal (100%) speed that expressions were displayed at and the average internal representation speed (happy = 123.19%; sad = 87.35%).

Another possible explanation for why autistic individuals have a particular difficulty recognising angry expressions relates to movement production. In our previous study[385], we used PLF videos that were created by filming four *non-autistic participants* posing different emotions. Given that autistic and non-autistic individuals may produce different facial expressions of emotion[146,147], and that one's own movement patterns influence the interpretation of the movement of others[353-356], the autistic participants in our previous study might have exhibited reduced emotion recognition accuracy because the non-autistic expressions were dissimilar to expressions that autistic individuals would adopt themselves. That is, in addition to the process (outlined above) of matching visual expression stimuli to internal templates, participants may motorically simulate observed expressions and "read off" the corresponding emotion label[407-409] (though note that this process is not essential for emotion recognition[410]). If the motoric simulation is associated with an unsuitable emotion label emotion recognition accuracy would be reduced. Since internal visual representations and motor programs are formed through different experiences (primarily the experience of observing others' expressions, and the experience of executing and refining actions until they achieve the desired goal) and one has relatively little experience of observing (and therefore forming visual representations based upon) one's own facial expressions, it is possible that autistic individuals could have internal motor programs for angry expressions that differ from those in the general population, without have differing internal visual representations. If a mismatch in the production of facial expressions is to explain autistic individuals' difficulty recognising angry expressions, one would expect to see that these groups differ more in their production of angry relative to happy and sad expressions. This seems plausible since Faso and colleagues[265] identified that the angry expressions posed by autistic, relative to non-autistic, individuals were rated (by non-autistic raters) as more intense (and there were no group differences in the intensity of posed happy and sad expressions). Therefore, it could be the case that autistic angry expressions are *more intense* (e.g., are faster or jerkier), and therefore this group struggle to read the *less intense* non-autistic expressions. Further research is necessary to a) characterise the expressive differences of autistic and non-autistic individuals, and b) ascertain whether these differences underpin an emotion-specific difficulty with angry expressions. In addition, this line of investigation requires further work to determine the direction of causality. It could be the case that autistic and non-autistic individuals produce different facial expressions and this leads to bidirectional emotion recognition difficulties, but it is also possible that difficulties with perceiving and labelling emotional facial expressions impacts on the production of emotional expressions.

In addition to the implications for the autism literature, we believe that our results have important implications for the study of emotion recognition more generally. Previous research has demonstrated that when *experimenters* speed-up PLF expressions, observers are more accurate in anger and happiness judgements and, when *experimenters* slow-down PLFs, observers are more accurate in their judgments of sadness[239]. To date, however, no research has investigated the speed of *observers'* internal representations of dynamic emotional expressions. Our findings, that participants increased speed (relative to the natural speed at which actors executed these expressions) for happy and angry, and decreased speed for sad expressions, suggest that people may have "caricatured" internal representations of emotion. In these caricatures, emotion-related kinematic cues are over-emphasised such that sad expressions appear extremely slow, and angry expressions appear extremely fast. Our results build on findings from the static emotion recognition literature wherein exaggerated internal representations of *static* expressions are common[388]. Our results also suggest a possible psychological mechanism for Sowden et al's observation that participants are more accurate in their recognition of slowed sad expressions and speeded happy and angry expressions[239]: slowed sad expressions and speeded happy/angry expressions may comprise a better match to participants' internal representations of these emotions, thus facilitating emotion recognition.

Limitations

The results of the current study are informative with respect to understanding emotion representations from facial motion cues alone. However, since many features of expressions are implicated in emotion processing, such as shading/depth[377] and pigmentation/colouring[376], one should be cautious to assume that our findings generalise to full dynamic emotional expressions (e.g., video recordings of facial expressions). It could be, for instance, that autistic and non-autistic individuals differ in the speeds they attribute to full emotional expressions but not point-light displays. However, given that our study was motivated by the observation of group differences in emotion recognition *from facial motion cues* (as isolated by PLF stimuli)[385], it was crucial to our overall research question that we used PLF stimuli in the current study. It is also important to note that autistic and non-autistic groups could in principle differ in their internal representations of facial expressions in the spatial (i.e., the configuration of facial features relative to one another) but not speed dimension. In line with this, Song and Hakoda[222] demonstrated that autistic individuals required a higher intensity of static angry, but not happy or sad, expressions in order for them to be correctly identified. Our choice to focus on the speed, rather than spatial, domain was driven by our empirically grounded *a priori* hypothesis that representations of anger would be characterised by higher speed movement.

With respect to the current study, it is also important to note that whilst we tested adults, the study by Song and Hakoda[222] focused on children (mean age was approximately 11.5 years). It is possible that there are developmental effects such that internal representations of emotion differ between autistic and non-autistic children but not between autistic and non-autistic adults. This is plausible since autistic children show less attention to faces than non-autistic children (as shown by a lack of an attentional bias to faces, less distraction by faces in visual search tasks, and lower fixation times [255,411,412]) and spend less time looking at heads/faces in a social scene than autistic adults[413]. Consequently, one may speculate that autistic children have atypical internal representations of emotion (at least in part due to reduced attention to faces), however, by the time they reach adulthood, they have gathered enough information about faces to have ‘typical’ emotion representations. At present, we cannot say whether we would have found group differences if our sample was made-up of children. Since the current study was motivated by our previous work with adult autistic participants[385] our focus on an adult sample was necessary. To establish whether there are developmental changes in internal representations of emotional expressions further work, which compares the development of autistic and non-autistic children, is necessary.

Conclusions

The current study aimed to estimate the speeds that autistic and non-autistic individuals attribute to angry, happy and sad dynamic facial motion. Whilst we found no group differences in the speeds attributed to happy and sad expressions (thus supporting our hypothesis), we also found no group difference for angry expressions (in conflict with our hypothesis). Consequently, we find no evidence to support the idea that particular difficulties with expression recognition from angry facial motion[385] are due to atypically fast (or slow) internal representations of anger. Future research is necessary to further unpack why autistic individuals display difficulties that are specific to angry expressions.

Chapter 4: The inside out model of emotion recognition: how the shape of one's internal emotional landscape influences the recognition of others' emotions

The previous chapter provided convincing evidence that there are no group differences in angry, happy and sad visual representations with respect to speed. These results force us to consider other factors which may be contributing to emotion recognition difficulties for autistic individuals. As discussed in the Introduction, constructionist[13,45], template-matching[108-112], and signal detection theories[140] raise the possibility that individuals with precise and differentiated information within their emotion concepts – for instance with respect to affective experiences and visual representations – may have a superior ability to recognise the emotions of other people. However, at present, research has not tested this idea. To investigate this possibility, it is necessary to first develop experimental tasks which facilitate measurement of the precision and differentiation of one's emotional experiences and visual emotion representations, and second assess the contribution of these factors to emotion recognition in the general population. If these variables predict emotion recognition performance, an important next step will be to compare autistic and non-autistic individuals on these factors (i.e., the precision and differentiation of emotional experiences and visual emotion representations), and to determine whether differences therein contribute to emotion recognition challenges for autistic people. Therefore, in the following chapter, across a series of experiments, we first develop and validate two novel paradigms examining the precision and differentiation of emotional experiences and visual emotion representations, and second build a mechanistic model linking the experience, visual representation and recognition of emotion, in a general population sample.

Publication 3:

The Inside Out Model of Emotion Recognition: How the Shape of One's Internal Emotional Landscape Influences the Recognition of Others' Emotions

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(Published in *Scientific Reports*)

Reference: Keating CT, Cook JL. The inside out model of emotion recognition: How the shape of one's internal emotional landscape influences the recognition of others' Emotions. Scientific Reports. 2023 Dec 6;13(1):21490. https://doi.org/10.1038/s41598-023-48469-8

Abstract

Some people are exceptional at reading emotional expressions, while others struggle. Here we ask whether the way we experience emotion "on the inside" influences the way we expect emotions to be expressed in the "outside world" and subsequently our ability to read others' emotional expressions. Across multiple experiments, incorporating discovery and replication samples, we develop EmoMap (N= 20; N=271) and ExpressionMap (N=98; replication N=193) to map adults' experiences of emotions and visual representations of others' emotions. Some individuals have modular maps, wherein emotional experiences and visual representations are precise and distinct- anger looks and feels different from happiness, which looks and feels different from sadness. In contrast, others have experiences and representations that are variable and overlapping- anger, happiness, and sadness look and feel similar and are easily confused for one another. Here we illustrate an association between these maps: those with precise and distinct *experiences* of emotion also have precise and distinct *visual representations* of emotion. Finally (N=193), we construct the *Inside Out Model of Emotion Recognition,* which explains 60.8% of the variance in emotion recognition and illuminates multiple pathways to emotion recognition difficulties. These findings have important implications for understanding emotion recognition in numerous clinical populations.

4.1. Introduction

Some people are exceptional at navigating the social world: the considerate concierge rapidly reads facial expressions and anticipates every desire; the perceptive companion accurately detects the sadness behind their friend's smile; the skilled negotiator notices a telling tightness around the eyes and knows just the right time to apply pressure. Other individuals struggle: as Parkinson's Disease progresses, people with this condition increasingly report challenges with reading others' emotional expressions[414], and similar difficulties predict negative social and wider health outcomes across a range of psychiatric and mental health conditions[415-417]. Despite clear individual differences in the ability to read others' emotional expressions, little is known about why these individual differences exist. Here we ask whether individual differences in navigating the social world of others' facial expressions are related to individual differences in the shape of one's own *internal* emotional landscape. In other words, is there a relationship between our experience of emotion "on the inside" and our ability to identify emotions in the "outside world"?

Internal "maps" of concepts - such as personality traits - can exert a considerable influence on judgments we make about others. Stolier and colleagues[418] for instance, mapped internal conceptual-trait maps by asking participants to rate the similarity of 13 different personality traits. They also mapped representations of how these traits are depicted on people's faces by asking participants to rate various face images with respect to these 13 traits[418]. Both internal (semantic) conceptual maps and external maps of facial representations, tended to exhibit a modular structure with particular traits - such as aggressive, mean, dominant and egotistical– clustering together[418]. Importantly, the shape of an individual's map of others' facial representations was highly correlated with the shape of their internal conceptual landscape such that a perceiver who believed aggression and dominance to be closely related in conceptual space would be more likely (compared to a perceiver with a weak link between the two concepts) to see an aggressive face as dominant[418]. Thus, Stolier and colleagues illustrate that, for trait judgements, internal conceptual maps and judgements we make about others in the outside world are tightly related[418].

Stolier and colleagues' work pertains to traits. Here we focus on emotions. Preliminary evidence provides initial support for a link between the experience and recognition of emotion. Israelashvili and colleagues[295] for example, illustrated that individuals who are good at differentiating their own experiences of distinct emotions are more accurate in reading others' emotional facial expressions. Nevertheless, although preliminary evidence indicates that individuals who are better able to identify how they feel "on the inside" are also better able to recognise emotions in the "outside world", it is unclear why this relationship exists. Afterall, recognising *one's own* emotions primarily depends upon the labelling of *internal signals*, whereas recognising *others'* emotions principally consists of categorizing *incoming sensory information*. The psychological mechanisms supporting superior emotion recognition in individuals with superior (own) emotion differentiation are currently unknown.

The face identity literature provides a candidate mechanism: studies from this field have illustrated that individuals who are good at face identity recognition tend to have robust visual representations (also referred to as templates and/or abstracted structural representations) of others' identities, in their minds eye[419-421]. Such representations are thought to be constructed via experience wherein exposure to different views of a face updates the abstracted structural representation of this identity and, over time, the representation comes to emphasise diagnostic aspects of the face (that differentiate this face from another) and minimise non-diagnostic aspects[421]. Signal detection theory (see [140]) also tells us that distinguishing between signal and noise (e.g., correct and incorrect facial identities) is easier if the signal and noise distributions are distinct and precise – when these channels are not overlapping, and when they are *consistent* across numerous instances or samples (i.e., narrow). In line with this, Etchells, Brooks and Johnston[421] found that participants were better at recognising faces from a novel view when they had built up a more precise representation of that face from multiple views, relative to a single view, during a preceding learning phase. Furthermore, it is well documented that faces that are more overlapping in appearance are more difficult to differentiate[286]. Therefore, the face identity literature raises the hypothesis that individuals who are adept at reading others' emotions will have *precise* and *distinct* visual representations (in their 'mind's eye') of emotional facial expressions. This hypothesis is yet to be tested.

If we are to understand why people who are better at recognising *others'* emotions tend to be good at identifying *their own*, and if this is related to the precision of visual representations of *others'* emotional expressions, we must also explain why representations would be more precise and distinct for individuals who are better able to differentiate their *own* emotions. Models of conceptual learning suggest that robust concepts facilitate learning: Having a (semantic) concept that a table has a flat top and four legs encourages a learner to focus on these invariant features when encountering new table exemplars and ignore variant features such as colour or texture[422,423], thus minimizing within-category differences and maximizing between-category differences[424]. Similarly, having precise and distinct concepts of *one's own* emotions (which may be multidimensional including semantic, interoceptive and sensory information [44,52-55,425]) may encourage a learner to focus on invariant features of facial expressions and ignore between expression variation, thus encouraging the formation of precise and distinct visual representations of *others'* facial expressions. However, despite theoretical justification for a link between the experience and representation of emotion, research has not yet tested this idea.

Here we ask whether the experience of emotion "on the inside" influences the way in which one represents the dynamic emotional facial expressions that one would encounter in the "outside world" and whether this, in turn, affects emotion recognition accuracy. Specifically, we predict that some individuals will have internal emotion maps with a clear modular structure, wherein emotional experiences are *precise* and *distinct*: happiness feels very different from anger, which feels very different from sadness. We predict that these individuals will also have *precise* and *distinct* representations of the way in which emotions are expressed on others' faces and, correspondingly, will be adept at recognising expressions. Other individuals, however, may have *variable* and *overlapping* experiences of emotion wherein anger, happiness and sadness feel relatively similar and are easily confused for one another. We predict that these individuals will have more *variable* and *overlapping* visual representations of others' expressions such that, in their mind's eye, anger, happiness and sadness look relatively similar. Thus, resulting in emotion recognition difficulties.

Across a series of experiments, we first develop and validate "EmoMap", a novel method to map the shape of individuals' emotional experience landscapes (Experiment 1). Second, we develop "ExpressionMap" to map the landscape of participants' visual representations of emotional expressions (Experiment 2). Following this, we test for a mapping between the experience of emotion "on the inside" and representations of the way emotions are expressed in the "outside world". That is, we ask whether those with modular internal emotional maps, who have precise and distinct experiences of anger, happiness and sadness, also tend to have precise and distinct visual representations of angry, happy and sad facial expressions (note that these emotions were selected as they correspond to different regions in the circumplex model of emotion[41], varying in both and valence). Throughout these analyses, we control for clinically relevant demographic factors known to be associated with the experience and perception of emotion (e.g., the level of autistic traits, the level of alexithymic traits, and non-verbal reasoning ability; e.g., [148,209,213,385,426-428]) to ensure that any relationships we discover exist even after accounting for these variables. Finally, we assess the contribution of the precision and differentiation (i.e., distinctness) of emotional experiences and representations to the recognition of anger, happiness and sadness, and use structural equation modelling to construct the 'Inside Out Model' of emotion recognition; a model which provides insight into the psychological mechanisms by which one's experience of emotions "on the inside" influences one's ability to identify emotions in the "outside world".

4.2. Results

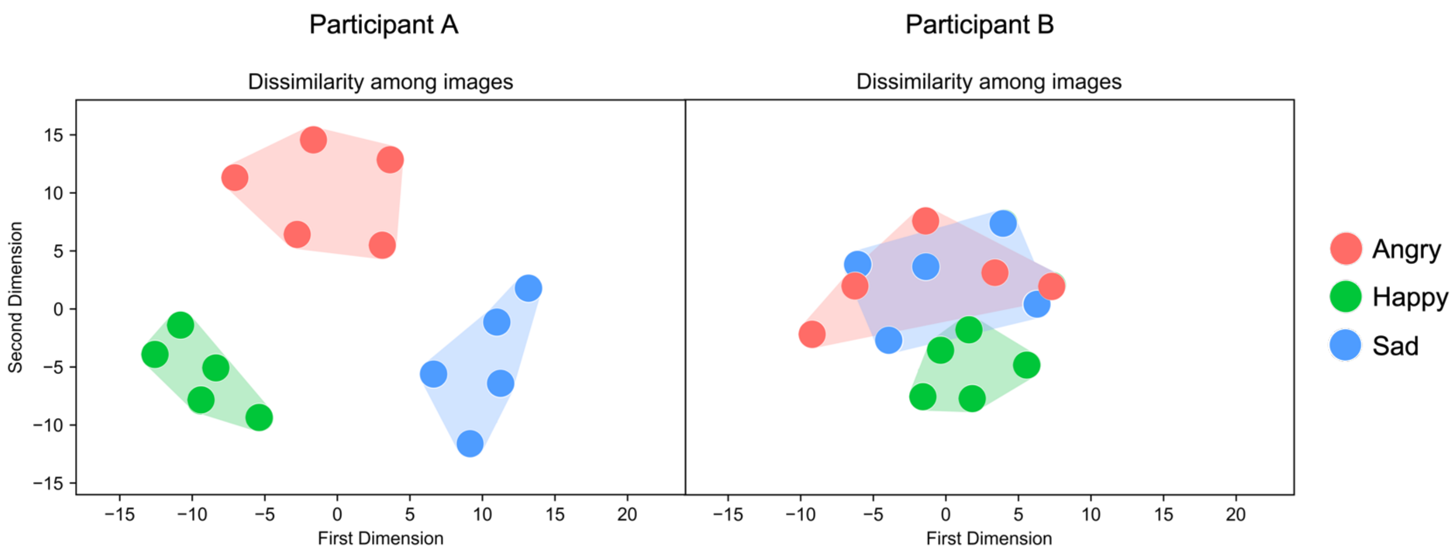
4.2.1. Study 1: Developing EmoMap

Participants (*N*=271) completed our EmoMap paradigm - a two-part task that assesses the differentiation and precision of emotional experiences. In the first part, on each trial, participants viewed pairs of images (from the Nencki Affective Picture System[429]) each known to selectively induce either anger, happiness or sadness[430], and were asked to rate how similar the emotions evoked by the images were on a scale from 0, 'Not at all similar', to ten, 'Very similar' (to 4 decimal places). These similarity scores were then transformed into distance scores via multidimensional scaling, a statistical technique that represents objects (emotional images, lexical items) as points in multidimensional space, wherein close similarity between objects corresponds to small distances between the points in the representation. Distance scores were then used to a) calculate the mean distances between (e.g., distance between angry and happy clusters, angry and sad clusters, and happy and sad clusters) and within emotion clusters, and b) plot multidimensional scaling maps.

The multidimensional scaling maps confirmed that the internal emotional landscape had a modular structure for some participants (Figure 4.1, left panel) and a less modular, more overlapping, structure for others (Figure 4.1, right panel). EmoMap was validated by illustrating that individuals high in alexithymic traits, who by definition have difficulties differentiating their own emotions[194], tended to have emotional landscape maps with a less modular, more overlapping structure, whereas those low in alexithymic traits had modular emotional landscapes. That is, linear mixed effects models predicting mean distance between clusters and mean distance within clusters with TAS score, AQ score, non-verbal reasoning ability (clinically relevant demographic variables known to be associated with the experience and perception of emotion; e.g., [148,209,213,385,426-428]), and with subject number as a random intercept revealed alexithymic traits as a significant negative predictor of distance *between* emotion clusters [$F(1,267) = -5.92$, $p<.05$] and distance *within* emotion clusters [$F(1,267) = -6.16$, $p<.05$]. In general, greater overlap was seen between anger and sadness [mean distance (SEM) = 14.39(0.21)], than happiness and anger [mean distance (SEM) = 20.79(0.29)], and happiness and sadness [mean distance (SEM) = 20.70(0.29)] in participants' internal emotional landscapes (see Appendix 3.1 for a full discussion). These results validate EmoMap by confirming that individuals who, by definition, have difficulties differentiating their own emotions exhibit higher EmoMap emotion confusion as indexed by smaller distances between- and within- emotion clusters (suggesting they have difficulties differentiating distinct and more similar emotional states).

Figure 4.1.

Examples of precise and distinct (left), and variable and overlapping (right) emotional landscapes.



Note. The dimensions illustrated here may somewhat reflect the two dimensions outlined in the circumplex model of affect[41] – arousal and valence. The first dimension may correspond to valence, with high values reflecting negative valence and low values reflecting positive valence (see left). The second dimension may correspond to arousal; high scores reflect high activation, and low scores reflect low activation (see left). This may be an appropriate interpretation of the internal emotional landscape of Participant A (left).

In the second part of EmoMap, on each trial participants were required to make decisions about three images (also from the Nencki Affective Picture System[429]). There were four conditions: one non-emotional control condition, and three emotional experimental conditions exploring the experience of anger, happiness and sadness respectively. Participants completed the control condition first. In this condition, participants were required to select which of the three (emotionally neutral) images they found most colourful using their mouse cursor. Two of these images were in colour and one was in grayscale, thus serving as an attention check. Following this, participants completed the three experimental conditions in a random order. In these conditions, participants were required to select which of the three images made them feel most angry, happy or sad using their mouse cursor (i.e., in the 'angry condition' participants would have to decide which image made them most angry). As in the control condition, there was a 'trap' image on each trial such that two of the images were strong inducers of the target emotion (e.g., sadness), and one was a strong inducer of another emotion (e.g., happiness), thus serving as an attention check. Emotional precision was calculated, for each emotion, based on the logical consistency of decision-making: if a participant selected image one over image two and image two over image three, but then selected image three over image one, this would be considered an inconsistent decision and would result in a reduction in their precision score[292] (see Methods for further details on scoring). Precision requires participants to differentiate between the intensity of emotion evoked by each image[292]. Therefore, inconsistent decisions are likely to stem from imprecision in an individual's emotional experience across repeated instances[292].

Using scores from this task, we aimed to determine whether there is a link between the precision and differentiation of emotional experiences. Our results illustrate that individuals with modular landscapes are more likely to have precise emotional experiences, whereas those with more overlapping emotion landscapes have less reliable emotional experiences. That is, a linear mixed effects model of emotional precision as a function of between-cluster distances, within-cluster distances, the interaction between emotion and between-cluster distances, the interaction between emotion and within-cluster distances (independent variables), AQ, TAS, non-verbal reasoning and colour (control) precision (control variables), with subject number as a random intercept revealed that emotional precision was positively predicted by between-cluster distances [$F(1,786.1) = 9.58$, $p<.01$], and negatively predicted by within-cluster distances [$F(1,785.9) = -10.30$, $p<.01$]. Since the emotion that was displayed (angry, happy or sad) did not interact with between- or within-cluster distances to predict emotional precision, our results suggest that those with larger distances *between* clusters and smaller distances *within* their emotion clusters typically had greater emotional precision for anger, happiness *and* sadness. Emotional precision was also positively predicted by non-verbal reasoning ability [$F(1,264) = 12.83$, $p<.001$] but not by any other variables, including colour control precision [all $p>.05$]. Hence, our results demonstrate that the distances between and within emotion clusters predict the precision of emotional experiences.

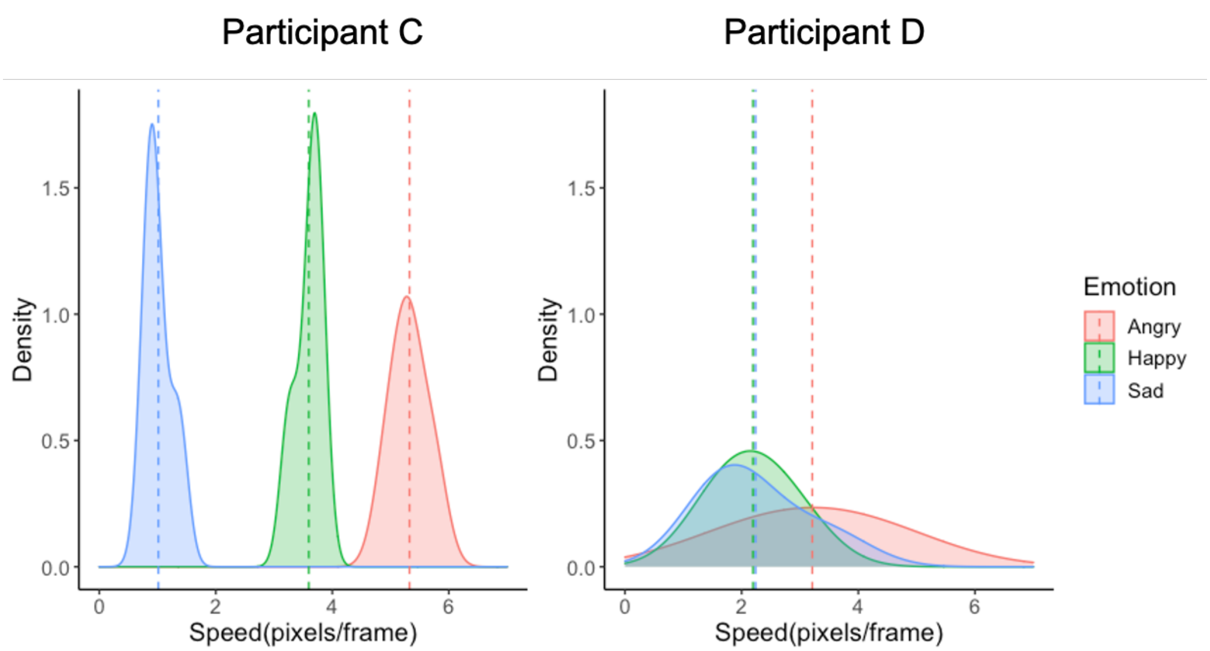
4.2.2. Study 2: Developing ExpressionMap

To map visual representations of the external expression landscape, participants (N=98; replication N=193) completed our ExpressionMap paradigm. On each trial participants were asked to move a dial to change the speed of an emotional point light display of the face (a PLF) until it matched the speed they typically associated with an angry, happy or sad expression. That is, participants were matching the speed of the displayed PLF to their visual representation of that expression. The precision of visual representations was indexed as the standard deviation of the speeds attributed to each repetition of the angry, happy and sad expressions respectively, multiplied by -1 (see Methods for full details). Mean representational precision was calculated by taking a mean of the precision scores for the angry, happy and sad PLFs. In addition, this task also provides an index of the 'distance' between emotions in participants' visual representations of facial expressions. Distance scores were calculated as the absolute difference in speed attributed to two different emotions. For example, to calculate distance between happy and angry, we subtracted the mean speed attributed to happy from the speed attributed angry, and then took the absolute value. Mean distance was calculating by taking a mean of the scores for the angry-happy, angry-sad, and happy-sad distances.

To visualise representations of the external emotional landscape, we produced density plots displaying the speeds attributed to angry, happy and sad expressions respectively. Density plots confirmed that for some individuals, visual representations of emotion are *precise* and *distinct* (Figure 4.2, left panel), and for others they are *variable* and *overlapping* (Figure 4.2, right panel). Across participants, the precision and differentiation of such representations differed as a function of emotion/emotion pair – these results are reported in Appendix 3.1 as they are outside the scope of the current study.

Figure 4.2.

Examples of precise and distinct and variable and overlapping visual emotion representations.

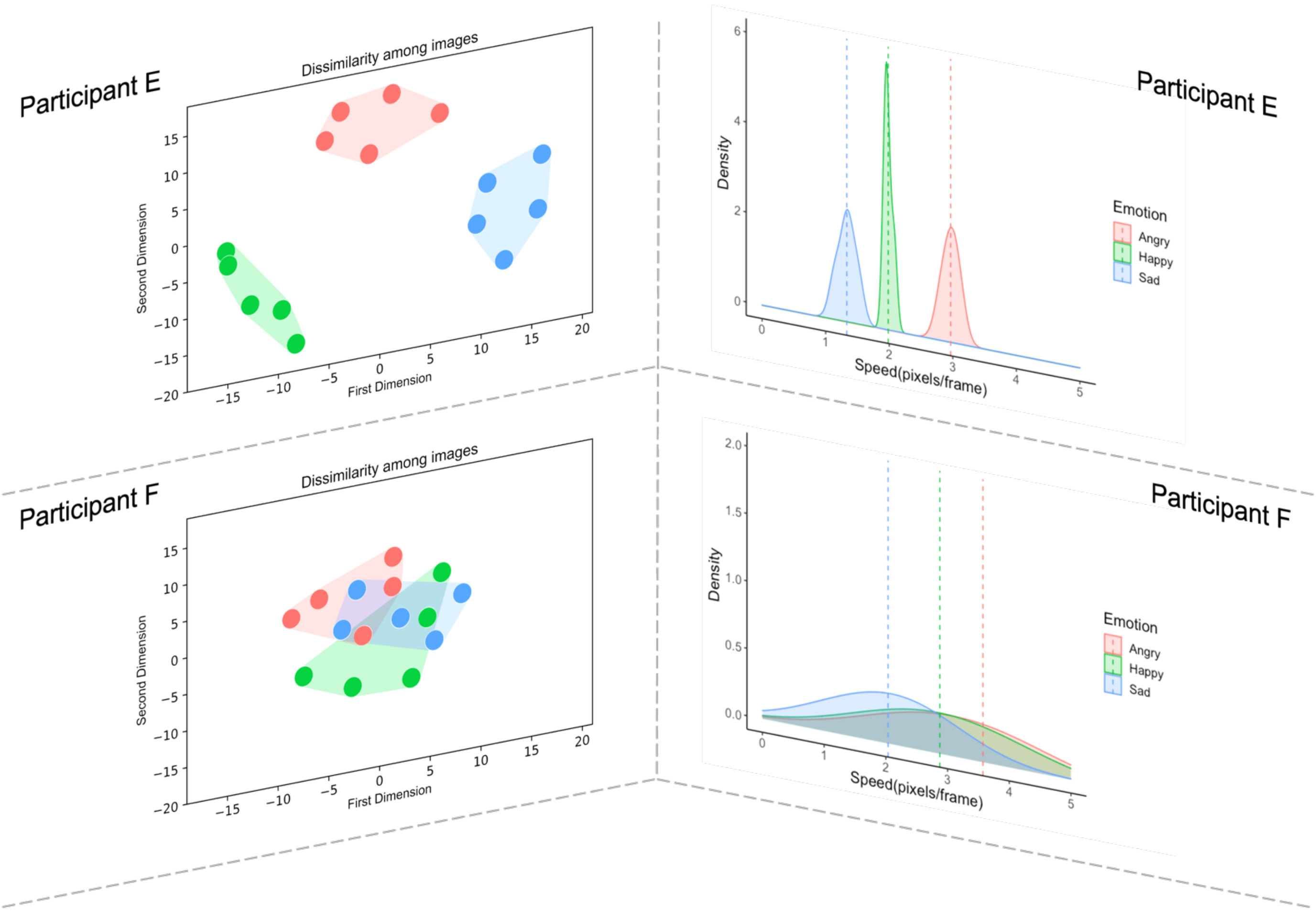


4.2.3. Mapping between the experience of emotion "on the inside" and their representations of emotional expressions in the "outside world"

A subset of participants (N =193) completed both EmoMap and ExpressionMap. To probe the existence of a mapping between the experience of emotion "on the inside" and representations of the way emotions are expressed in the "outside world", we constructed two separate linear mixed effects models to predict metrics of ExpressionMap (representational precision and distance between representations) from metrics derived from EmoMap (emotional precision, distance between emotion clusters respectively), with AQ score, TAS score, non-verbal reasoning, and control precision as control variables, and with subject number as a random intercept. Representational precision was positively predicted by emotional precision [$F(1,186) = 5.15$, $p<.05$] but not colour control precision [$p > .05$]: individuals with more precise experiences of emotion also had more precise visual representations of emotion (while the precision of colourfulness judgments did not contribute to the precision of visual representations). Non-verbal reasoning was also a significant predictor of representational precision [$F(1,186) = 30.71$, $p<.001$]: those with higher non-verbal reasoning had greater representational precision. In addition, distance between emotion representations was predicted by distance between emotion clusters [$F(1,186) = 8.19$, $p<.01$]: those with more distinct experiences of emotion also had more distinct representations. Thus, precision and differentiation within internal emotional landscapes is linked to precision and differentiation in visual representations of the external world (even after controlling for relevant participant demographics; see Figure 4.3).

Figure 4.3.

A diagram demonstrating that precision and differentiation within internal emotional landscapes (left) is linked to precision and differentiation in visual models of the external world (right).



Note. Figure 4.3 top shows the modular emotion and representation maps of one participant. Figure 4.3 bottom shows the overlapping emotion and representation maps of another participant.

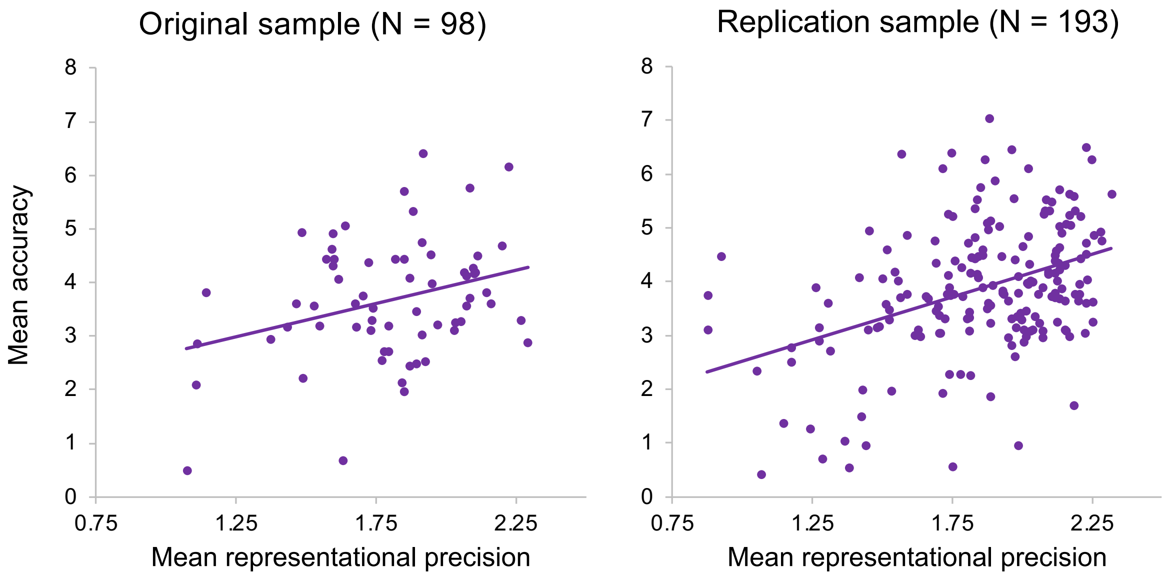
4.2.4. Predicting emotion recognition ability

The above analyses illustrate a mapping between the experience of emotion "on the inside" and visual representations of the way emotions are expressed in the "outside world", but how do these inside and outside maps influence emotion recognition accuracy? To answer this question, we first focused on asking how the shape of ExpressionMaps relate to individual differences in emotion recognition as indexed by our previously validated PLF Emotion Recognition Task[239,385]. On each trial in this task, participants viewed an angry, happy or sad PLF and rated how angry, happy and sad the expression appeared. Emotion recognition accuracy was calculated as the correct emotion rating minus the mean of the two incorrect emotion ratings.

Building on the face identity literature[419-421] and principles of signal detection theory[140] our *a priori* hypothesis was that emotion recognition accuracy would be positively predicted by the precision of emotion representations and by distance between emotion representations. To test this, we constructed a linear mixed effects model with accuracy as the outcome variable, representational precision, distance between emotion representations, the interaction between representational precision and distance, AQ score, TAS score and non-verbal reasoning as predictors (clinically relevant participant characteristics known to be involved in the experience and perception of emotion; e.g., [148,209,213,385,426-428]), and subject number as a random intercept. Across both our original (N=98) and replication (N=193) sample, representational precision was a significant positive predictor of accuracy [original sample: $F(1,91) = 4.19$, $p<.05$; replication sample: $F(1,186) = 13.86$, $p<.001$; see Figure 4.4]: those with more precise visual emotion representations typically achieved higher accuracy (i.e. identified the emotion that the actor intended to convey) on the PLF Emotion Recognition Task. In conflict with our hypothesis, accuracy was not predicted by distance in either sample [all $p>.05$]. There were also no other significant predictors of accuracy across both samples [all $p>.05$].

Figure 4.4.

The relationship between mean accuracy and mean representational precision in original sample (left [R = -.311, p = .002, BF_{10} = 15.32]) and replication sample (right [R = -.399, p < .001, BF_{10} = 1.21e^6]).

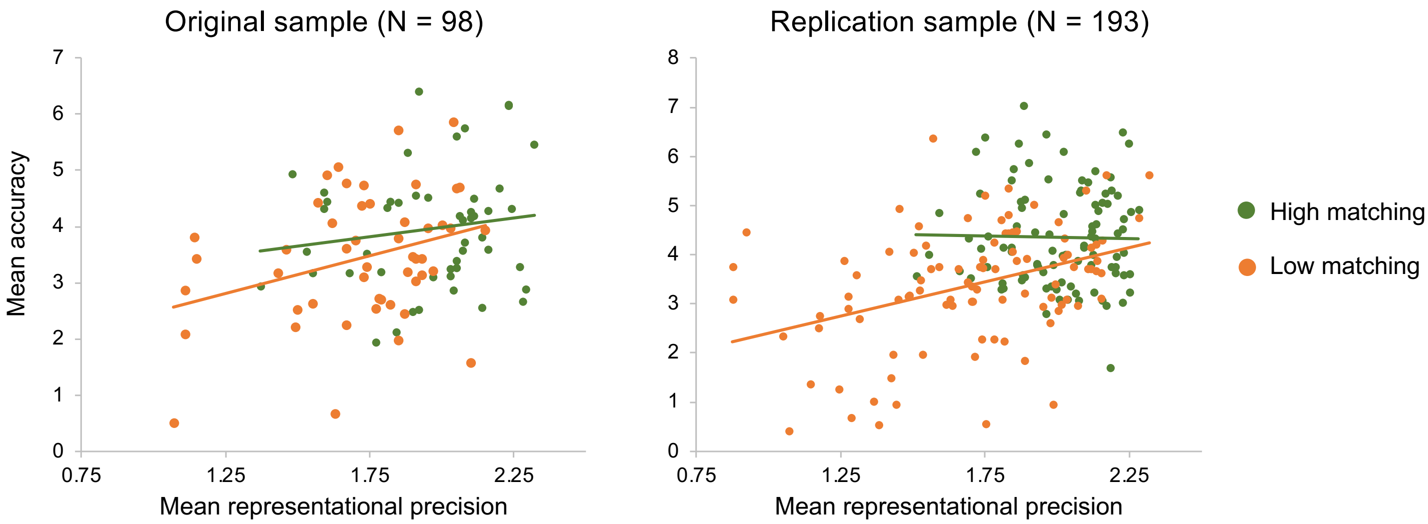


Since it is likely that emotion recognition is contingent not only on the clarity of emotion representations but also on the ability to match a displayed expression to one's visualization, we also included a visual matching task in our battery. This task assesses how well participants can visually match the speed of one expression to another displayed expression. Each trial began with a PLF stimulus video on the left-hand side of the screen. After this video had played once, the same PLF stimulus video also appeared on the right-hand side of screen (moving at a random speed) and continued to play in a loop. Participants were instructed to "move the dial to change the speed of the video on the right until it matches the speed of the video on the left". Consequently, participants were visually matching the speed of one PLF to another. Deviation scores (the distance between the speeds of the two animations) comprised the absolute value of the percentage speed attributed to the leftward expression minus that attributed to the rightward expression. Mean deviation scores comprised a mean of all of the absolute deviation scores. Higher deviation scores represented greater difficulties matching the two expressions.

Subsequently, visual matching difficulty and the interaction between representational precision and matching difficulty were added to the linear mixed effects model described above. In our larger sample, we found that the main effect of representational precision on emotion recognition accuracy was moderated by matching difficulty [$F(1,184) = 12.26$, $p<.001$]. To unpack this interaction, we conducted a median half split analysis, dividing participants into a high matching group (matching deviation scores <27.75%) and a low matching (matching deviation scores >27.75%) group. Representational precision was only a significant predictor of accuracy for those with lower matching ability [$F(1,89) = 7.16$, $p<.01$], and not those with higher matching ability [$F(1,90) = 0.44$, $p=.507$] (see Figure 4.5). This interaction was also evident in our original sample [low matching: $F(1,42) = 4.18$, $p<.05$; high matching: $F(1,42) = 0.44$, $p=.513$]. Hence, across both samples, for participants with a lower ability to match expressions, representational precision was a significant predictor of emotion recognition ability. This potentially indicates that when one's ability to match two representations is compromised, having clear and precise visual representations becomes particularly important.

Figure 4.5.

The relationship between mean accuracy and representational precision within the high (original sample: $R = .148$, $p = .310$, $BF_{10} = 0.294$; replication sample: $R = .004$, $p = .972$, $BF_{10} = 0.13$) and low matching groups (original sample: $R = 0.324$, $p < .05$, $BF_{10} = 2.18$; replication sample: $R = .379$, $p < .001$, $BF_{10} = 176.06$).



In sum, emotion recognition ability is predicted by the precision of imagined visual representations of others' emotions and one's matching ability, such that – for individuals with lower ability to match two visually displayed expressions - the more precise one's representations the better one's emotion recognition accuracy.

4.2.5. Building the Inside Out Model of Emotion Recognition (N = 193)

For the following analyses, we focused on the 193 participants that had completed all four tasks (EmoMap, ExpressionMap, Visual Matching and PLF Emotion Recognition), thus allowing us to build a comprehensive model incorporating the experience, representation and recognition of emotion. Model construction comprised a four-step process. First, since we had many potential variables of interest, we determined their relative importance for emotion recognition using a random forests analysis[431] employing the Boruta wrapper algorithm[432]. In this analysis, representation matching, matching difficulty, representational precision, distance between emotion clusters, and emotional precision were deemed important for emotion recognition. Here, 'representation matching' reflects the interaction between representational precision and matching difficulty, which was found to be a significant predictor of emotion recognition in our previous analyses. 'Representation matching' was computed by multiplying the representational precision scores for angry, happy and sad expressions with their corresponding matching difficulty scores (e.g., angry representational precision x angry matching difficulty; happy representational precision x happy matching difficulty; sad representational precision x sad matching difficulty). Higher representation matching scores indicate superior representational precision, matching ability, or both. Following our random forests analysis, we added variables classified as "important" into a structural equation model predicting emotion recognition accuracy, sequentially (starting with the most important variable), until there was no longer a significant improvement (or our goodness of fit index exceeded the specified threshold). Third, to determine the most mathematically plausible path directions in our structural equation model, we systematically reversed each path and compared the Bayesian Information Criterion (BIC) scores for the original and reversed models (see Appendix 3.2 for the steps listed above). Lastly, we built one final structural equation model in which we included the path directions that were mathematically most plausible. There was moderate to very strong evidence that this final model was better than all previous models (BIC difference > 6). Fit indices demonstrated that our final model was a good fit for the data [Root Mean Square Error of Approximation (RMSEA) = 0.055; Standardized Root Mean Square Residual (SRMR) 0.071; Comparative Fit Index (CFI) = 0.954].

In our final structural equation model (see Figure 4.6 and Table 4.1), which accounted for 60.8% of the variance in emotion recognition accuracy, there were two component processes that contributed to individual differences: the *precision component* and the *differentiation component*. With respect to the former, emotional precision exerted an indirect effect on emotion recognition [z = 2.05, *b* = 0.53, *p*<.05], by influencing representation matching ability [z = 2.06, *b* = 0.75, *p*<.05], which had a direct effect on emotion recognition accuracy [z = 6.93, *b* = 0.70, *p*<.001]. With respect to the latter, our analysis revealed that there were significant direct effects of (1) distance between emotion clusters on emotion recognition accuracy [z = 2.18, *b* = 0.20, *p*<.05], and (2) emotion recognition accuracy on distance between emotion clusters [z = 2.47, *b* = 0.24, *p*<.01], thus suggesting a bidirectional feedback loop between these variables. In addition, whilst distance between representations had a direct effect on distance between emotion clusters [z = 2.93, *b* = 0.28, *p*<.01], it did not exert an indirect effect on accuracy [z = 1.80, *b* = 0.05, *p*=.072]. Finally, our analysis also identified a significant direct effect of emotional precision on non-verbal reasoning ability [z = 2.21, *b* = 0.63, *p*<.05], and of alexithymia on distance between clusters [z = -2.27, *b* = -0.15, p<.05; see Appendix 3.3 for the inter-relationships between all variables in the model].

Table 4.1.

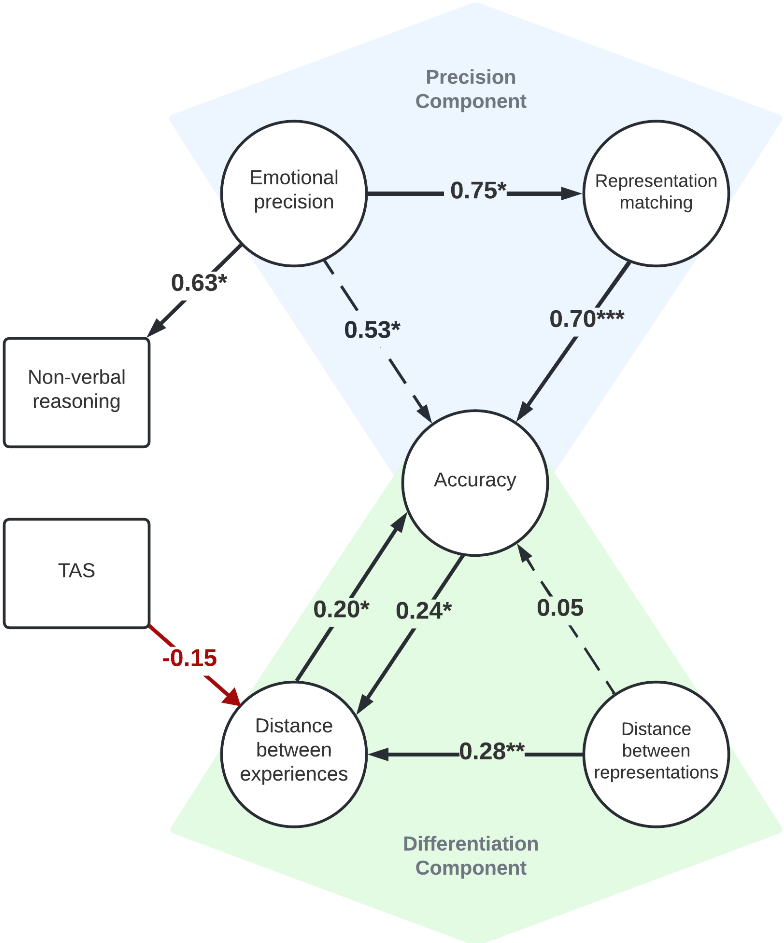
Parameter estimates for our final structural equation model. Standardised betas are shown in the final column (Std. b).

Path	Estimate	z-value	*p*-value	Std. *b*
Representation Matching → Accuracy	0.021	6.932	< .001	0.700
Emotional Precision → Representation Matching	4.393	2.137	= .033	0.754
Emotional Precision → Representation Matching → Accuracy *	0.090	2.052	= .040	0.527
Emotional Precision → NVR	0.018	2.205	= .027	0.633
Distance between clusters → Accuracy	0.039	2.179	= .029	0.197
Accuracy → Distance between clusters	1.193	2.466	= .014	0.236
Distance between representations → Distance between clusters	2.611	2.932	= .003	0.275
Distance between representations → Distance between clusters → Accuracy *	0.102	1.800	= .072	0.054
TAS → Distance between clusters	-0.058	-2.269	= .023	-0.150

Note. Indirect effects are labelled with an asterisk (*)

Figure 4.6.

The final structural equation models exploring the experience, visualization and recognition of emotion.



Note. Circles correspond with latent variables; rectangles correspond with manifest variables. Black arrows indicate positive relationships. Red arrows indicate negative relationships. Full line arrows correspond with direct effects; dashed line arrows correspond with indirect effects. The values displayed are the standardised beta path coefficients. The significance level for direct and indirect effects are shown by asterisks: $^*p < .05$, $^{**}p \leq .01$, $^{***}p \leq .001$.

4.3. Discussion

Here we illustrated that individual differences in the experience of emotion "on the inside" are interrelated with individual differences in representations of emotional expressions, and that these sources of individual differences predict 61% of the variance in accuracy on a dynamic emotion recognition task. In Experiment 1 we developed (N=20) and validated (N=271) "EmoMap", a novel method to map the shape of individuals' emotional experience landscapes. In Experiment 2 we developed "ExpressionMap" to map the landscape of (N=98; replication N=193) participants' representations of how emotions are expressed in the outside world. Subsequently we tested for a mapping between the experience of emotion "on the inside" and their representations of the way emotions are expressed in the "outside world". Individuals with modular internal emotional maps, who had precise and distinct emotional experiences, tended to have precise and distinct visual representations of other people's dynamic emotional facial expressions. Structural Equation Modelling further illustrated that such individuals tended to have correspondingly enhanced emotion recognition accuracy. Therefore, our "*Inside Out Model of Emotion Recognition"* provides new insight into the psychological mechanisms underpinning individual differences in the recognition of emotion from dynamic facial expressions.

In our final model, which explained 60.8% of the variance in emotion recognition accuracy, there were two component processes that contributed to individual differences: the *precision component* and the *differentiation component*. Within the precision component, which explained a larger proportion of the variance in emotion recognition, those with less precise emotional experiences also had less precise visual emotion representations, and correspondingly low emotion recognition accuracy. Interestingly, representational precision only contributed to emotion recognition for those with a lower ability to match two visually displayed expressions. With respect to the differentiation component, having poorly differentiated representations of others' expressions, predicted poorly differentiated experiences of anger, happiness and sadness and corresponding difficulties with emotion recognition (note that this later link between experience and recognition of emotion was bidirectional). The direction of all the paths in our model was determined through systematic comparison of BIC scores. BIC comparisons revealed moderate to very strong evidence that the directions in our final model were the most mathematically plausible. Nevertheless, it is important to note that structural equation modelling cannot definitively determine causality[433]. Thus, any directions of causality suggested by our model are merely hypotheses that should be tested via causal manipulation[356].

Taking a step back from the individual path directions, it is pertinent to consider the *component processes* outlined in our final model. Although our modelling allowed for other pathways to emotion recognition difficulties – for example an emotion pathway (emotional precision, distance between clusters) and a representation pathway (representational precision, distance between representations) – our analyses demonstrated that the *precision* and *differentiation* component processes were the most mathematically plausible. The emergence of these components is somewhat surprising given that EmoMap and Expression map were completed in two separate sittings (on two separate days) and that different methods were used to calculate their corresponding variables (see Method). The emergence of these components *despite* their corresponding variables being calculated differently and measured across different sittings suggests that they are meaningful components of emotion recognition rather than methodological artefacts.

More generally, it is useful to consider alternative explanations for our conclusion that individual differences in emotion recognition from dynamic stimuli can, in part, be explained by individual differences in the way emotions are experienced and the way expressions are represented. A primary question concerns whether a third variable unrelated to emotion, such as participants' motivation to do well, underpins the relationships between the experience, representation and recognition of emotion. In other words, do those with more precise experiences of emotion also have more precise visual emotion representations and more accurate emotion recognition simply because these individuals tried harder on all tasks? Our findings suggest that this is unlikely: self-reported effort was not significantly associated with emotional precision, representational precision, distance between representations, matching difficulty, or representation matching, respectively (all $p > .05$; see Appendix 3.4). In addition, although there were small-moderate correlations between effort and distance between clusters [$R = .272$, $p < .001$], and effort and emotion recognition accuracy [$R = .236$, $p = .001$] respectively, our Bonferroni-corrected partial correlations demonstrated that all the relationships we discovered remained significant after controlling for self-reported effort (see Appendix 3.4). Hence, the relationships we found between the experience, representation and recognition of emotion are not underpinned by self-reported effort. Similarly, since each of our paradigms included intricately designed attention checks, it is unlikely that differences in attention underpin the associations between these variables. Finally, one may ask whether the relationships documented here pertain specifically to the processing of emotion. That is, could it be that some individuals have precise and distinct concepts in general and hence they are good at recognising any complex stimuli. Our results suggest that this possibility is also unlikely: only those with precise experiences of emotion, and not those with precise concepts of colour, had greater representational precise and emotion recognition accuracy (see Appendix 3.2). Hence overall, it is unlikely that effort, attention, or another domain general process (e.g., having distinct concepts in general) underpins the associations found here. Rather our results, which have been acquired across several experiments with large samples (involving built-in replications), provide convincing evidence for links between the experience, representation, and recognition of emotion.

But how do such links come about? For example, why would having imprecise emotional experiences lead to imprecise expression representations? As noted in our Introduction section, constructionist theories offer a theoretical framework that may help answer such questions. Constructionist theories of emotion (e.g., [44,52-55,425]) propose that children are continually constructing multimodal representations of emotions. For example, when hearing a caregiver describe a situation as "anger inducing" a child may associate their current internal sensations and prevailing visual/auditory/tactile inputs with the word "angry". Over time "angry" ceases to be just a word and becomes a multimodal concept[44] and once the concept is acquired, it may function to sharpen its own conceptual boundaries[424]. That is, having precise and distinct emotion concepts may help a learner focus on invariant features of facial expressions and ignore between expression variation, thus encouraging the formation of precise (i.e., reliable) and distinct visual representations of others' expressions. Note that the reverse direction of causality is also possible: a child with precise visual representations of others' expressions may be better able to recognise when others are angry thus providing the child with a label with which to categorise their own internal states. Such a child may have more opportunities for labelling their internal states, potentially resulting in more precise and distinct emotional experiences. As mentioned previously, further work must test the Inside Out Model's directions of causality if we are to make more confident claims about the causal role of emotional experience in the precision of visual emotion representations, and develop richer theoretical models of the developmental experiences that give rise to such links.

In addition to contributing to constructionist theories of emotion, our findings are also relevant to the face identity and signal detection literatures[419-421]. By demonstrating that precise visual representations of emotional expressions facilitate recognition of emotional expressions, we illustrate an important role for stored visual representations in *emotion* recognition, that extends beyond the known role of representations in facial *identity* recognition. Our findings are also partially in line with signal detection theory[140]. That is, we identified that emotion recognition was directly predicted by the precision, but not the differentiation, of visual emotion representations. These findings raise the possibility that there are independent contributions of these factors to emotion recognition. The lack of a significant (direct) effect of the differentiation of visual emotion representations (i.e., the distance between attributed speed) on recognition may be due to the presence of large differences in the speeds attributed to angry, happy, and sad facial expressions [angry mean(SEM) = 3.85(0.06); happy mean(SEM) = 2.80(0.04); sad mean(SEM) = 1.63(0.03)], meaning that on average the representations are 'far apart' and instances of overlap between the signal and noise distributions are relatively uncommon. Independent of this there may feasibly be an additional effect of the precision of visual emotion representations (variation in attributed speeds). For example, the expectation literature would predict that more precise (i.e., a representation that is precise in appearance across instances) representations of upcoming stimuli would precipitate increased recognition accuracy (see [434-437]). Future research should aim to include other emotions (e.g., surprise, disgust, and fear), likely to populate other points on the speed continuum, to identify whether this illuminates an effect of the differentiation of visual emotion representations. In the current study, we were unable to include additional emotions due to testing constraints. Including surprise, disgust and fear would have increased the duration of our test battery to over eight hours (doubling the current testing time of four hours) and compromised our ability to test such large samples (due to limits on resources). We selected high and low arousal (anger/ happiness and sadness), and positively and negatively valenced (happiness and anger/sadness) emotions to cover different regions in arousal-valence space[41].

Implications

Our Inside Out Model raises a number of testable hypotheses that may help us better understand the aetiology of the emotion recognition difficulties documented in numerous clinical conditions (e.g., depression, anxiety, psychosis, eating disorders, Parkinson's disease, and autism spectrum disorder; see [141-146,438]). In the current study, we have illuminated two component processes that may contribute to these difficulties: the differentiation component and the precision component. With respect to the former, differences in recognising others' emotions may be linked to difficulties differentiating one's own emotional states; indeed preliminary evidence supports this pathway in the context of depression, anxiety, schizophrenia, anorexia nervosa and autism (as found in [148,439-443]). The precision component, on the other hand, suggests the testable hypothesis that emotion recognition difficulties in clinical conditions linked to imprecise emotional experiences – such as bipolar disorder and psychosis, which are associated with mood fluctuations[151,444] – may be mediated by the (im)precision of visual representations of emotional expressions. Identifying mechanistic pathways that explain variation in emotion recognition may help us design tailored support systems with potential impacts upon psychosocial adjustment[254] and psychological health and wellbeing[255]. Hence, future studies should aim to test these predictions.

Limitations

The results of the current study are informative with respect to understanding the links between the experience, visual representation, and recognition of emotion from facial motion cues alone. Here, we have employed point-light displays, which provide a way of studying core dynamic cues (e.g., speed), while controlling other perceptual dimensions[445,446], such as identity (e.g., gender, age, ethnicity, face attractiveness), depth, and pigmentation, which are all known to influence emotion recognition[376,377,447]. Although this allowed us to accurately assess the contribution of kinematic cues to visual emotion representations, and their subsequent effect on emotion recognition accuracy (without these other cues confounding the results), such tight control may limit the extent to which our findings generalise to full dynamic emotional expressions (e.g., full video recordings of facial expressions). It could be, for example, that the links we have demonstrated between the experience, representation and recognition of emotion exist for point-light displays, but not full emotional expressions. However, since individuals compare incoming facial expressions to stored templates, which represent the average facial expressions they have encountered previously (e.g., the average angry expression across all previous encounters[108-111,448]), it seems unlikely that the precision of such templates would only be important when recognising emotion from point-light displays (which are not typically encountered). Concurrently, there is no clear reason why an individual would draw on their own emotional experiences to recognise emotion, specifically in point light displays, and not in full dynamic expressions. Nevertheless, future studies are necessary to confirm whether our results generalise to full emotional expressions.

Relatedly, it is also worth noting that here we examine the precision and differentiation of visual emotion representations specifically in the speed domain. This was an active design choice, motivated by previous evidence demonstrating the critical role of speed cues in the visual representation[449] and recognition[239,385] of emotion. Nevertheless, in future work, we will expand our paradigms to encompass other spatiotemporal emotion cues (e.g., degree of spatial exaggeration, movement onset/offset, texture, colour, etc.), thus facilitating investigations into the precision and differentiation of visual emotion representations in other domains.

It is also important to consider the limitations of our EmoMap paradigm for assessing the experience of emotion. Although his paradigm has several methodological advantages – it can be completed online in just 25-35 minutes and does not require participants to translate their emotional experiences into words (see [450]) – there are disadvantages of using such computer-based assessments. For example, by employing images to elicit emotional reactions (as is common in the literature e.g., [148,295,428,451,452]), participants may respond based on how they think they *should* feel, rather than how they truly feel. Whilst this is a possibility, we specifically addressed this issue in our task instructions, thus minimizing the likelihood of participants responding in this way: when describing EmoMap, we told participants that “this isn’t about what the image represents, or how you think other people, on average, respond to the images. It is about your own personal response” (as in Huggins et al[292]). Nevertheless, future investigations could benefit from employing more ecological methods such as experience sampling (e.g., [453,454]), wherein participants label or rate their emotional state on several occasions throughout the day for multiple days. Using these methods, emotion differentiation can be calculated by computing intra-class correlations, measuring consistency between emotion ratings across occasions, for each participant (see [293]). Such studies could then aim to test whether the ability to differentiate emotions in everyday life is associated with more differentiated visual emotion representations, and enhanced emotion recognition.

Finally, it is important to highlight the limitations of our study with respect to sample generalizability. Across both experiments discussed here, the samples were predominantly female (74.91, 46.94, and 78.76% respectively), white (58.67, 83.67, and 56.48% respectively), and from the United Kingdom (37.27, 64.29, and 41.97% respectively). Since there may be differences in the experience and recognition of emotion between males and females[455-457], it may be that the results discussed here are not representative of males. Although this is possible, the evidence from our post-hoc analyses suggest that our primary effects are not moderated by sex (see Appendix 3.5). Thus, it seems that for both males and females the experience, visual representation, and recognition of emotion are all linked. Nevertheless, further work should aim to verify our results in more balanced, and/or male, samples. In addition, previous studies have found that experiences (e.g., [458-462]) and visual representations (e.g., [388,389,463-465]) of emotion vary across cultures. Many of these studies suggest that there may be differences specifically in the *appearance* of visual representations (e.g., individuals from Western Cultures emphasise the eyebrows and mouth in their visual representations, while those from East Asian cultures the eye region[388]). Although this is an important consideration, it is worth noting that, in the current study, we specifically focus on the precision and differentiation of visual representations, rather than on the appearance of them. Since individuals across numerous cultures employ template-matching techniques (i.e., comparing incoming facial expressions to stored 'templates') to recognise the emotions of others[108-111,448], it seems unlikely that the *precision* of such templates would be important in one culture but not another. Nevertheless, future studies should aim to the Inside Out Model across different cultures.

4.4. Method. Experiment 1: Developing EmoMap

This study was approved by the Science, Technology, Engineering and Mathematics (STEM) ethics committee at the University of Birmingham (ERN_16-0281AP9D) and was conducted in accordance with the principles of the revised Helsinki Declaration. Informed consent was obtained from all participants.

4.4.1. Participants

271 participants were recruited via the School of Psychology's Research Participation Scheme database and Prolific. Individuals were eligible to take part in the study if they were between the ages of 18 and 65, fluent in English, had normal or corrected-to-normal vision, and had access to a computer/laptop with an internet connection. The sample size was based on an *a priori* power analysis conducted using G*power[402]. To replicate the association between

alexithymia and emotion differentiation in Erbas et al[428], 97 participants were required to have 95% power at alpha level 0.05. However, since effect sizes are commonly inflated[342], and we were utilizing a more complicated analysis (a linear mixed effects model in which we control for the other relevant demographic variables known to be associated with the experience and perception of emotion), we recruited a larger number of participants (N = 271; almost triple the sample size generated in our power calculation).

Participant characteristics are displayed in Table 4.2. Information regarding participants' ethnicities is reported in Appendix 3.6. Notably, four participants in the sample (1.48%) reported that they had a diagnosis of autism spectrum disorder. Therefore, we conducted our analyses twice, first including these participants and then excluding them. Since the general pattern of results was unaffected by their removal, we included these participants in our final statistical analyses.

Table 4.2.

Means and standard deviations of participant characteristics. In the column on the right-hand side, means are followed by standard deviation in parentheses.

Variable	Participants (N=271)
Sex	68 Male, 203 Female
Age	24.00 (9.16)
NVR	60.22% (15.35%)
AQ-50	19.11 (6.85)
TAS-20	48.17(12.08)

4.4.2. Procedures

Participants completed demographics questions, followed by the Autism Quotient[304] (see Chapter 2 for a description) and Toronto Alexithymia Scale[344] (see Chapter 2) on Qualtrics (https://www.qualtrics.com). Subsequently, participants completed our EmoMap paradigm (openly available at https://app.gorilla.sc/openmaterials/447800) followed by the Matrix

Reasoning Item Bank[343] (see Chapter 2) on Gorilla (https://gorilla.sc). All participants completed the study online.

4.4.3. Materials and Stimuli

EmoMap Task

There were two key parts of the EmoMap task. In the first part, on each trial participants viewed pairs of images from the Nencki Affective Picture System[429], and were instructed to "think about what feelings arise when you look at each of these images. Now please rate how **SIMILAR** those two feelings are". Participants made their ratings on a visual analogue scale (with a step size of 0.0001) ranging from 0, 'Not at all similar' to 10, 'Very similar'. An advantage of the EmoMap paradigm is that it provides a tool to measure emotion differentiation without requiring participants to produce emotion labels, unlike existing tasks (see [449] for a for a full discussion).

The chosen images were known to be effective at selectively inducing anger, happiness or sadness across large samples (N = 124)[430], and generated distinct emotion clusters based on graph theory analyses with pilot study data (see Appendix 3.7). In this task, there were five images for each emotion (anger, happiness and sadness) resulting in 15 different images and 105 unique image combinations (and therefore 105 trials): 30 within emotion-category combinations (10 for anger, 10 for happiness and 10 for sadness) and 75 between emotion-category combinations (25 angry-sad, 25 angry-happy, 25 happy-sad). A reaction time check was incorporated to prevent participants responding too quickly (i.e., without thinking). Responses faster than 1000ms resulted in an error message ("Too Fast. Our algorithm has detected that you might need to take longer to think through your answer. You will now incur a 5 second penalty and then will be asked to do the trial again"), a 5-second penalty, and then the trial was re-started. This threshold was selected to give participants sufficient time view the images, detect and compare the emotions evoked each by them, and then respond by clicking on the scale.

To map the shape and size of participants' internal emotional landscapes, similarity ratings were transformed into (Euclidean) distance scores through multidimensional scaling (using the Scikit-learn library in Python). Multidimensional scaling (MDS) is a statistical technique that represents objects (emotional images, lexical items etc.) as points in multidimensional space wherein close similarity between objects corresponds to close distances between the corresponding points in the representation[466]. The distance between points in multidimensional space can then be plotted (see Figure 4.1). Mean distances within specific emotion clusters comprised the average of the Euclidean distances for the 10 angry-angry, 10 happy-happy and 10 sad-sad image pairs, respectively. Mean distances between specific emotion clusters comprised the mean of the Euclidean distances for the 25 angry-happy, 25 angry-sad, and 25 happy-sad image pairs, respectively. We then computed mean distances within and between clusters by averaging across emotions/emotion pairs. Larger distances between and within emotion clusters reflect greater emotion differentiation.

The second part of our EmoMap paradigm was inspired by the work of Huggins and colleagues[292]. In this part of the task, on each trial, participants were presented with three images from the Nencki Affective Picture System[429], and were required to make a decision. This task involved four conditions: one non-emotional control condition, and three emotional experimental conditions exploring the experience of anger, happiness and sadness respectively. First, participants completed the non-emotional control condition. In this condition, participants were required to select which of the three (neutral) images they found most colourful using their mouse cursor. Two of these images were in colour and one was in grayscale, thus serving as an attention check. If participants selected the grayscale image, they were presented with an error message, incurred a 5-second penalty, and then were asked to do the trial again. Following this, participants completed the three experimental conditions in a random order. In these conditions, participants were required to select which of the three images made them feel most angry, happy or sad (e.g., in the angry condition, participants had to decide which of the three images made them most angry) using their mouse cursor. As was the case in the control condition, there was a 'trap' image on each trial in the emotional conditions. On each trial, two of the images were strong inducers of the target emotion (e.g., sadness), and one was a strong inducer of another emotion (e.g., happiness), thus serving as an attention check. If participants selected the image that strongly induced the non-target emotion, they were presented with the error message discussed above, incurred a 5-second penalty, and then were asked to do the trial again. Within each condition, there were 11 target (i.e., non-trap) images which were presented in all possible unique pairs across 55 trials. The images that were selected had previously been identified as successful inducers of the target emotion[430]. In addition, in order to make the experimental conditions comparable, we ensured that the mean intensity ratings (angry = 3.53; happy = 3.50; sad = 3.56) and standard deviation of intensity ratings across images within a condition (angry = 0.80; happy = 0.80; sad = 0.81) were similar for each emotion.

Precision scores were calculated for each condition in line with the logical consistency of a participants' decisions. To demonstrate this, consider a participant that selects image one over image two and image two over image three; both of these decisions are consistent with one another. However, if the participant then selected image three over image one, this would be considered inconsistent with their previous judgments[292]. Precision requires participants to differentiate between the intensity of emotion evoked by each image[292]. Thus, here inconsistent decisions likely stem from imprecision in how individuals experience an emotion across multiple instances[292].

We followed the procedures of Huggins et al[292] to calculate precision. We first quantified each participant's image rankings by summing the number of times they chose each image. If a participant was completely consistent in their decisions within a condition, rank scores would follow a linear hierarchy: the image that was most emotionally evocative (or colourful) should be chosen in all ten trials it appeared (scoring 10), the second-highest should be chosen in nine of ten trials (scoring 9), and so on, the image they found least emotionally intense (or colourful) should never be chosen (scoring 0). Subsequently, we examined how image rankings related to the decisions made on each trial. Images with higher ranks should evoke stronger emotional reactions than those with lower ranks. Thus, inconsistent decisions occur when an image with a lower ranking is chosen over an image with a higher ranking. For each trial, item differences were calculated as the rank score for chosen item minus the rank score for the unchosen item. For inconsistent decisions, the item difference score would be equal to or less than zero. More extreme inconsistencies (e.g., selecting the image with the lowest ranking over the one with the highest ranking) resulted in more negative item differences. We then summed the item differences for each condition, to produce total precision scores, with greater scores reflecting higher precision. If a participant made completely consistent decisions within a condition, their score would be 220.

4.5. Method. Experiment 2: Developing ExpressionMap

4.5.1. Participants

The first ("original") sample for Experiment 2 comprised 98 participants recruited via Prolific. The second, replication, sample comprised 193 participants recruited via the School of Psychology's Research Participation Scheme database and Prolific. For both samples, individuals were eligible to take part if they were between the ages of 18 and 65, fluent in

English, had normal or corrected-to-normal vision, and had access to a computer/laptop with Google Chrome and an internet connection. The sample size for our replication sample was based on an *a priori* power calculation using GLIMMPSE[341]. To have 90% power to replicate our finding from sample one that representational precision predicted emotion recognition accuracy, 68 participants were necessary (alpha level = 0.05). Since effect sizes are commonly inflated[342] and using larger samples improves the precision of parameter estimates[467], we recruited a larger number of participants (N = 193; almost triple the sample size generated in our power calculation).

Participant characteristics are displayed in Table 4.3. Information regarding participants' ethnicities is reported in Appendix 3.5. Notably, one participant in the original sample (1.02%) and two participants in the replication sample (1.02%) reported that they had a diagnosis of autism spectrum disorder. Therefore, we conducted our analyses both including, and then excluding, these participants. Since the general pattern of results was unaffected by their removal, we included these participants in our final statistical analyses.

Table 4.3.

Means and standard deviations of participant characteristics. In the column on the right-hand side, means are followed by standard deviation in parentheses.

Variable	Experiment 2, Original sample (n=98)	Replication sample (n=193)
Sex	52 Male, 46 Female	41 Male, 152 Female
Age	33.34 (9.79)	23.41 (9.04)
NVR	58.45% (16.62%)	61.24% (14.79%)
AQ-50	18.65 (7.64)	18.94 (6.79)
TAS-20	46.00(11.82)	48.13 (11.58)

4.5.2. Procedures

First, informed consent was obtained from all participants before conducting the study. Participants in the original sample completed demographics questions, followed by the 50-item

Autism Quotient[304], and the 20-item Toronto Alexithymia Scale[344] on Qualtrics (https://www.qualtrics.com). Following this, these participants completed three tasks that employed dynamic point light displays (a series of dots that convey biological motion) of angry, happy and sad facial expressions (PLFs) on Gorilla (https://gorilla.sc). Participants completed ExpressionMap followed by the Visual Matching task, followed by the PLF Emotion Recognition task (see Chapter 2 for a full description). Finally, participants completed the MaRs-IB[343] (see Chapter 2 for a full description). For those in the replication sample, participation was split across two parts. In part one, participants completed demographics questions, the AQ, TAS and EmoMap paradigm. In part two, which was completed in a separate sitting at least 24 hours after finishing part one, participants completed ExpressionMap, the Visual Matching Task, the PLF Emotion Recognition task, and the MaRs-IB. For both samples, all parts of the study were completed online.

4.5.3. Materials and Stimuli

ExpressionMap

In this task, on each trial, participants were presented with a dynamic point light display of the face (PLF; on average approximately 6 seconds in length) that looped such that it played continuously. Participants were instructed to "move the dial to change the speed of this video until it matches the speed of a typical ANGRY/HAPPY/SAD expression".

The PLFs were originally created by asking actors to read a sentence ("my name is John and I'm a scientist") in a happy, angry or sad manner[239]. The emotion depicted in the stimulus video matched the instructed emotion, i.e., on a trial where an angry facial expression was presented, participants were only asked to manipulate the speed of the video so that it matched the speed of a typical angry expression. Consequently, participants were matching the speed of the displayed PLF to their imagined visual representation of that expression (the speed they would imagine "in their mind's eye"). Participants could change the speed of the video by moving a dial clockwise to increase the speed of the animation or anticlockwise to decrease the speed of the animation. The minimum and maximum point on the dial corresponded with 25% and 300% of the recorded speed respectively. Once participants were satisfied, they pressed the spacebar to continue. There was no time limit for participants to respond on each trial. Participants were shown four repetitions of each PLF stimulus video (each one starting at a random speed) across four actors. This resulted in 16 videos per emotion (4 actors x 4 repetitions x 3 emotions = 48 trial in total). Participants completed three practice trials (one for each emotion at 100% starting speed) and then the 48 randomly ordered experimental trials across three blocks. Participants were encouraged to take breaks between blocks.

The ExpressionMap task was adapted from Keating, Sowden and Cook[449] (Chapter 3). In the current study we improved the task by a) using a dial, instead of the slider used previously, thus making the minimum and the maximum points on the scale more ambiguous, b) starting each video at a random speed thus reducing potential response biasing, c) setting the initial dial position to a random orientation that did not correspond to starting speed, thus ensuring that the minimum and maximum points, and the point of the 100% recorded speed were at different spatial locations on the dial – as a result, participants were unable to be consistent simply by selecting a similar location on the scale each time –, d) incorporating a reaction time check- when participants responded faster than 5 seconds on a trial, they were presented with an error message, incurred a 5 second penalty, and then were asked to do the trial again and, e) incorporating a walk-through video to facilitate comprehension of task instructions.

Whereas existing methods aim to construct comprehensive representations of emotional expressions (e.g., [384,463,464]), ExpressionMap seeks to assess accompanying features of those representations (e.g., speed, precision and differentiation; see [468]). ExpressionMap provides an index of the percentage speed attributed to each of the stimulus videos by participants (e.g., if a participant attributes 130% speed to an expression, their representation for that expression is 1.3 times faster than the recorded speed). Following the procedures outlined in Keating, Sowden and Cook[449], we calculated the true speed attributed to each of the PLFs (in pixels per frame) by multiplying the percentage speed attributed, divided by 100, with the speed of the actor's facial movement in the original video. For example, for a trial in which a participant attributed 200% speed to a face moving at 2.5 pixels/frame, the true speed attributed to the expression would be 5 pixels/frame [i.e., $(200 \div 100) \times 2.5$] (see [449] for more information).

This task operates on the premise that, compared to participants with precise visual representations, those with less precise representations of emotion would attribute more variable speeds to the expressions[469]. For instance, someone with a precise visual representation of anger would attribute similar speeds across repetitions (e.g., by attributing 120% speed, 121% speed and 119% speed to the angry expression). In contrast, someone with a less precise visual representation would be more variable (e.g., by attributing 120% speed, 60% speed and 180% speed to an angry expression). Therefore, to index the precision of visual emotion representations, we took the standard deviation of the speeds attributed to one emotion for one actor (i.e., actor 1, angry expression) across the 4 video repetitions. Following this, we multiplied standard deviation scores by -1 so that our variable would now represent precision (note that in Figures 4.4 and 4.5 we also added a constant of 2.52, since the lowest score was -2.52, to facilitate interpretation). We then calculated mean representational precision for each of the emotions (angry, happy and sad) by taking a mean of the precision scores for each actor within an emotion (e.g., taking a mean of the precision scores for angry expressions across actors 1, 2, 3 and 4). Mean representational precision was calculated by taking a mean of the precision scores for the angry, happy and sad PLFs.

Finally, this task also provides an index of the ‘distance’ between emotions in participants’ visual representations of facial expressions. To calculate distance scores, we subtracted the speed attributed to one emotion from the speed attributed to another and then took the absolute value of this number. For example, to calculate distance between happy and angry, we subtracted the speed attributed to happy from the speed attributed angry, and then took the absolute value. Mean distance was calculated by taking a mean of the scores for the angry-happy, angry-sad, and happy-sad distances.

Visual Matching Task

We reasoned that an individual might have beautifully precise mental representations of others’ expressions and still struggle to recognise others’ emotions due to an inability to match the incoming expression data with the stored representation. Thus, we developed the Visual Matching task to assess how well participants can visually match the speed of one expression to another (displayed) expression. Each trial began with a PLF stimulus video on the left-hand side of the screen. After this video had played once, the same PLF stimulus video also appeared on the right-hand side of screen, moving at a random speed, and continued to play in a loop. Participants were instructed to “move the dial to change the speed of the video on the right until it matches the speed of the video on the left”. Turning the dial clockwise increased speed, anticlockwise movements decreased speed. The minimum and maximum points on the dial corresponded with 25% speed and 300% of the recorded speed respectively (participants were not explicitly informed about this). Once the participant was satisfied, they pressed spacebar to continue. Participants were shown four repetitions of each PLF stimulus video for each of the four actors; each repetition had a different starting speed. In each full set of 16 (4 actors x 4 repetitions) stimulus videos for an emotion, the starting speed ranged from 50% to 200% of the recorded speed, in 10% increments (i.e., 50%, 60%, 70%, 80%, 90%, 100%, 110%, 120%, 130%, 140%, 150%, 160%, 170%, 180%, 190%, 200%). This range of starting speeds ensured that participants were able to match across a variety of speeds. Participants completed three practice trials (one for each emotion at 100% starting speed) and then the 48 randomly ordered experimental trials across three blocks. Participants were given the opportunity to take breaks between blocks.

The Visual Matching task provides an index of how well participants can visually match the speed of one expression to another. To calculate deviation scores, we subtracted the percentage speed attributed to the expression on the right from the percentage speed of the video on the left and took the absolute value of this deviation score as a measure of how far away the speeds of the two animations were (irrespective of whether they attributed too high or too low speed). Finally, we calculated mean deviation scores by taking a mean of all of the absolute deviation scores. Higher deviation scores representation greater difficulties matching the two expressions.

4.5.4. Transparency and openness

In this manuscript, we report how we determined our sample sizes, all data exclusions, all manipulations, and how we calculated all measures. All datafiles, data-processing code, analysis scripts, and tasks are openly available at https://osf.io/hd8u2/wiki/home/. The data were processed and analysed using R (R Studio version 2021.09.2), Python (Jupyter Notebook version 6.4.8), and JASP (version 0.16). All our linear mixed effects models were conducted in R Studio using the lmer function (from the *lme4* package). For these models, we also used the Anova function (from the *car* package) to conduct a Type III ANOVA with a Kenward-Roger[470] approximation for degrees of freedom, as supported by Luke[471]. For all linear mixed effects models, the relationships between the experience, representation, and recognition of emotion hold when the control variables are included (as reported in the Results section) and excluded, thus affording us greater confidence in our findings. In R Studio, we also conducted a random forest analysis[431] employing the Boruta wrapper algorithm (Boruta function from *Boruta* package[432]), and structural equation modelling using the sem() function (from the *lavaan* package). In JASP, we conducted Bayesian linear regressions (using a default Jeffreys-Zellner-Siow prior; r scale = 0.354) to determine the relative strength of evidence for the experimental versus null hypotheses. For these analyses, we followed the classification scheme used in from Lee and Wagenmakers[352]: BF_{10} values between one and three represent weak evidence, between three and ten moderate evidence, and greater than ten strong evidence, for the experimental hypothesis.

Chapter 5: Autistic adults exhibit highly precise representations of others' emotions but a reduced influence of emotion representations on emotion recognition accuracy

In Chapter four, we demonstrated that the ability to precisely visualise and match facial expressions contributed to emotion recognition for non-autistic people. As such, our results illuminate potential candidate mechanisms that may underpin the emotion recognition difficulties of autistic individuals. It could be, for example, that autistic individuals have less precise visual emotion representations, a poorer ability to visually match two expressions, or both, thus leading to emotion recognition difficulties (e.g., with anger[147,191,219-223]). The following chapter tests this possibility, first comparing the precision and differentiation of visual emotion representations and matching ability between groups (after controlling for alexithymia), and second assessing the contribution of these factors to emotion recognition for both autistic and non-autistic people.

Publication 4:

Autistic adults exhibit highly precise representations of others' emotions but a reduced influence of emotion representations on emotion recognition accuracy

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(Published in *Scientific Reports*)

Reference: Keating CT, Ichijo E, Cook JL. Autistic adults exhibit highly precise representations of others' emotions but a reduced influence of emotion representations on emotion recognition accuracy. Scientific Reports. 2023 Jul 22;13(1):11875. https://doi.org/10.1038/s41598-023-39070-0

Abstract

To date, studies have not yet established the mechanisms underpinning differences in autistic and non-autistic emotion recognition. The current study investigated whether autistic and non-autistic adults differed in terms of the precision and/or differentiation of their visual emotion representations and their general matching abilities, and second, explored whether differences therein were related to challenges in accurately recognising emotional expressions. To fulfil these aims, 45 autistic and 45 non-autistic individuals completed three tasks employing dynamic point light displays of emotional facial expressions. We identified that autistic individuals had more precise visual emotion representations than their non-autistic counterparts, however, this did not confer any benefit for their emotion recognition. Whilst for non-autistic people, non-verbal reasoning and the interaction between precision of emotion representations and matching ability predicted emotion recognition, no variables contributed to autistic emotion recognition. These findings raise the possibility that autistic individuals are less guided by their emotion representations, thus lending support to Bayesian accounts of autism.

5.1. Introduction

Autism spectrum disorder (ASD) is a neurodevelopmental disorder, characterised by restricted and repetitive interests and difficulties with social communication and interaction[151]. While not considered a core diagnostic feature, emotion recognition has been a topic of interest in autism research for over 30 years because it is often thought that challenges in this area might be an underlying cause for social difficulties. However, findings in this literature are famously mixed (see [146] for a review): some studies find differences in emotion recognition between autistic and non-autistic people, some studies find no differences and some find quite specific difficulties (e.g. with angry expressions [147,191,219-222,385]). In this literature it is often the case that "emotion recognition" is treated as a unitary or modular ability. However, recent work has begun to elucidate several component processes that contribute to individual differences in emotion recognition. Here we 1) compare autistic and non-autistic individuals on various abilities which we know to be involved in (non-autistic) emotion recognition, and 2) test whether these processes also contribute to emotion recognition in autistic adults. Understanding the extent to which different tasks rely on these factors might help us to disentangle the mixed findings in this literature.

Recent work has highlighted that a person's internal templates - that is the way one pictures emotional expressions in the "minds' eye" (also known as a *visual representations* of emotion; e.g., [384,388,463,464,472]) - are important contributors to emotion recognition accuracy (Chapter 4)[473]. Signal detection theory (see [140]) tells us that at least two properties of visual representations should predict emotion recognition accuracy: precision and differentiation. That is, a 'signal' distribution and a 'noise' distribution that are both imprecise (wide) and indistinct (overlapping) provide low sensitivity to discriminate between 'signal' and 'noise'. Thus, an individual with an imprecise visual representation of anger, which overlaps with the representation of sadness should find it difficult to discriminate between the two emotions. Our recent work tested this hypothesis by asking (non-autistic adult) participants to manipulate a dial to change the speed of a dynamic point light face (PLF) stimulus (depicting an actor speaking in a happy, angry or sad fashion) until it moved at a speed they typically associated with an angry, happy or sad expression[473]. Thus, providing us with an estimate of the speed of participants' internal visual representations of emotional expressions. Participants also completed an emotion recognition task in which they rated the extent to which PLF stimuli depicted different emotional expressions[473]. Although we did not confirm a role for differentiation in emotion recognition, we did find (across two samples with a total N = 281) that adults with less precise emotion representations typically exhibited lower emotion recognition accuracy scores[469,473]. Thus, signal detection theory highlights two features of visual emotion representations that may be important in emotion recognition: 1) the precision, and 2) the differentiation of these visual representations. Our empirical work to date has confirmed an important role for precision.

In addition to precision, our previous work showed that the general ability to match two images also plays an important role in emotion recognition. We theorized that to have superior emotion recognition, one may need to have a) precise representations of facial expressions, *and* b) the ability to *match* incoming expression stimuli to internal representations. To test matching, we asked participants to alter the speed of a PLF until it matched the speed of a second PLF[473]. Across both a discovery and replication sample, we found an interaction between representational precision and matching ability. That is, for participants with a good ability to visually match two expressions, representational precision was less important for emotion recognition. In contrast, if participants had a poorer ability to match expressions, representational precision played an important role.

In a parallel literature, there is preliminary evidence that autistic individuals struggle to differentiate their own emotions[148]. Since autistic individuals may struggle with emotion differentiation they may also struggle to differentiate *visual representations* of emotion. That is, autistic individuals may picture emotional expressions in their mind's eye as more similar and overlapping than their non-autistic peers (e.g., the angry and sad expressions they imagine look very similar and are easily confused for one another). This is particularly plausible given that individuals with less differentiated *experiences* of emotion typically have less differentiated *visual representations* too[473]. As mentioned previously, since overlapping 'signal' and 'noise' distributions may make it difficult to discriminate the 'signal' from the 'noise'[140], it may be that difficulties differentiating *visual representations* are responsible for emotion recognition differences in autism. However, research has not yet tested this idea.

In sum, recent work has begun to elucidate a number of factors that could account for individual differences in emotion recognition, including the precision and differentiation of visual representations of expressions and visual matching ability. It follows that emotion recognition difficulties in autism could be due to differences in one, or many, of these factors. For instance, autistic individuals may have more imprecise and/or overlapping visual representations of emotional expressions. Unpacking this may help to explain why not all studies find differences between autistic and non-autistic people with respect to emotion recognition: perhaps some emotion recognition tasks rely more on either the precision or differentiation of visual emotions representations, or more on these representations in general, than others. For example, affect matching paradigms, in which participants judge whether two expressions show the same or different emotions may place less emphasis on visual emotion representations (as participants compare expressions that are *presented* to them sequentially or simultaneously) than labelling paradigms, where participants may have to compare to their visual representations in order to produce the correct emotion label.

The current study therefore, first investigated whether autistic and non-autistic adults differed with respect to the precision and/or differentiation of their visual representations of emotion and their general matching abilities (in the speed domain), and second explored whether differences therein were related to individual differences in accurately recognising emotional expressions. In our study, we also controlled for alexithymia – a subclinical condition wherein individuals experience difficulties in identifying their own emotions[194] – to ensure that any differences between the groups relate to autism, and not to alexithymia, as has been found in previous work[207,209,212,213].

Recent Bayesian accounts of autism propose another possible source of differences in emotion recognition in autism. According to Bayesian accounts, prior expectations bias the perception of incoming sensory information. With respect to emotion recognition, if one expects to observe a happy expression, one will attend more to features that generally signal happiness and less to features that tend to signal other emotions[406]. Bayesian theories of autism argue that autistic people are less affected by prior expectations than neurotypical people[259,260] and place greater emphasis on incoming sensory information (see [261]). Therefore, for non-autistic people, expectations can bias the perception of expressions (i.e., incoming sensory stimuli) such that they better match visual representations of expected emotions. For autistic people the perception of expressions may be less affected by prior expectations, and therefore their perception of the incoming expression may be less biased towards their visual emotion representation. If it is the case that autistic individuals are less affected by their visual representations of emotion (relative to non-autistic people), we would expect emotion recognition accuracy to be predicted by the precision and differentiation of these representations to a lesser extent than for non-autistic individuals. Consequently, in addition to investigating whether autistic and non-autistic adults differ in terms of matching abilities, the precision and/or differentiation of visual emotion representations, we also assessed the extent to which a number of different abilities were implicated in autistic and non-autistic emotion recognition.

5.2. Results

To determine whether there are differences between autistic and non-autistic individuals in these abilities, the current study employed three tasks involving dynamic point light displays of angry, happy and sad facial expressions. The first task was an adapted version of our "ExpressionMap" task[449,468,473] which uses a method of adjustment design. On each trial, participants were required to manipulate a dial to speed-up or slow-down PLF stimuli until they matched their visual representation of anger, happiness, and sadness. This task assesses how precise (by assessing variability, across trials, in attributed speed) and overlapping (via assessing the mean distance between emotions in terms of speed) participants' visual emotion representations are. In the second task, known as the "Visual Matching Task"[473], participants were required to match the speed of a PLF to another displayed PLF. Since participants are provided with a visual representation to match to, they do not need to imagine anything, therefore this task indexes visual matching ability independent of imagination ability. Finally, we used our previously validated task[239,385] to index emotion recognition ability. On each trial, participants viewed an angry, happy, or sad PLF and rated the extent to which the expression looked angry, happy and sad on visual analogue scales. Emotion recognition accuracy was calculated as the correct emotion rating minus the mean of the two incorrect emotion ratings.

In the following section, we (1) compare autistic and non-autistic participants on the precision and differentiation of visual emotion representations, matching abilities, and emotion recognition, and (2) determine whether the same processes are implicated in autistic and non-autistic emotion recognition.

5.2.1. Analyses comparing autistic and non-autistic participants

First, to compare the precision of visual emotion representations (as measured by the ExpressionMap task) across participant groups, we conducted a linear mixed effects model with representational precision as the dependent variable, emotion (angry, happy, sad), group (autistic vs non-autistic), the interaction between emotion and group [independent variables], age, sex, non-verbal reasoning ability and alexithymia [control variables] as predictors, and subject number as a random intercept. This revealed that there was a significant main effect of emotion [$F(2,176) = 87.13$, $p < .001$]: precision scores were highest for sad [mean(standard error of the mean; SEM) = -0.52(0.03)], followed by happy [mean(SEM) = -0.68(0.04)], followed by angry expressions [mean(SEM) = -0.91(0.04)]. In addition, both age [$F(1,83) = -18.23$, $p < .001$], and non-verbal reasoning [$F(1,83) = 18.10$, $p < .001$] predicted representational precision. Most importantly, however, we identified a main effect of group [$F(1,83) = 6.25$, $p = .014$]: in contrast to our hypothesis, the autistic participants [mean(SEM) = -0.64(0.04) exhibited significantly higher precision than the non-autistic [mean(SEM) = -0.77(0.04)] participants, suggesting that autistic individuals have more precise visual representations of emotion. The emotion x group interaction [$p = .594$], sex [$p = .207$], and alexithymia [$p = .469$] were not significant predictors of representational precision.

Next, to compare the distances between emotion representations across participant groups, we constructed a linear mixed effects model with distance as the dependent variable, emotion pair (angry-happy, angry-sad, happy-sad), group (autistic, non-autistic), the interaction between emotion pair and group [independent variables], age, sex, non-verbal reasoning, and alexithymia [control variables] as predictors, and subject number as a random intercept. In line with the results from our previous study [30], this analysis found that there was a significant main effect of emotion [$F(2,176) = 74.31$ $p < .001$]: the distance between angry and sad emotion representations was largest [mean(SEM) = 2.25(0.11)], followed by angry and happy [mean(SEM) = 1.21(0.09)] and happy and sad [mean(SEM) = 1.14(0.07)]. There was no main effect of group [$p = .117$], nor an interaction between emotion pair and group [$p = .317$], thus autistic and non-autistic individuals do not significantly differ in the differentiation of visual emotion representations. Finally, age [$p = .080$], sex [$p = .174$], non-verbal reasoning [$p = .390$] and alexithymia [$p = .594$] did not predict the distance between emotion representations.

Next, to compare the matching difficulty of the autistic and non-autistic participants, we ran a linear mixed effects model of matching difficulty as a function of emotion (angry, happy, sad), group (autistic, non-autistic), the emotion x group interaction [independent variables], age, sex, and non-verbal reasoning [control variables] as predictors, and subject number as a random intercept. This analysis revealed that non-verbal reasoning ability was a significant negative predictor of matching difficulty [$F(1,83) = -15.75$, $p < .001$]: those with higher non-verbal reasoning had a greater ability to match two visually displayed expressions on speed. Importantly, there was no significant main effect of group [$p = .255$] or an emotion x group interaction [$p = .795$], indicating that autistic and non-autistic individuals had similar matching ability across all emotions. There was also no significant main effect of emotion [$p = .058$]. Age [$p = .188$], sex [$p = .388$], and alexithymia [$p = .149$] were also not significant predictors of matching difficulty.

Finally, we constructed a linear mixed effects model of emotion recognition accuracy (as measured by the PLF emotion recognition task) as a function of emotion (angry, happy, sad), spatial level (50%, 100%, 150% spatial exaggeration), kinematic level (50%, 100%, 150% speed), group (autistic, non-autistic), the interaction between these variables [independent variables], age, sex, non-verbal reasoning, and alexithymia [control variables] as predictors, and subject number as a random intercept. This revealed that there was no significant main effect of group or any significant interactions with group (all $p > .05$). Therefore, the autistic and non-autistic participants exhibited comparable levels of accuracy across different emotions, speeds, and levels of spatial exaggeration. The remaining results from this analysis are reported in Appendix 4.1 as they are outside the scope of the current study.

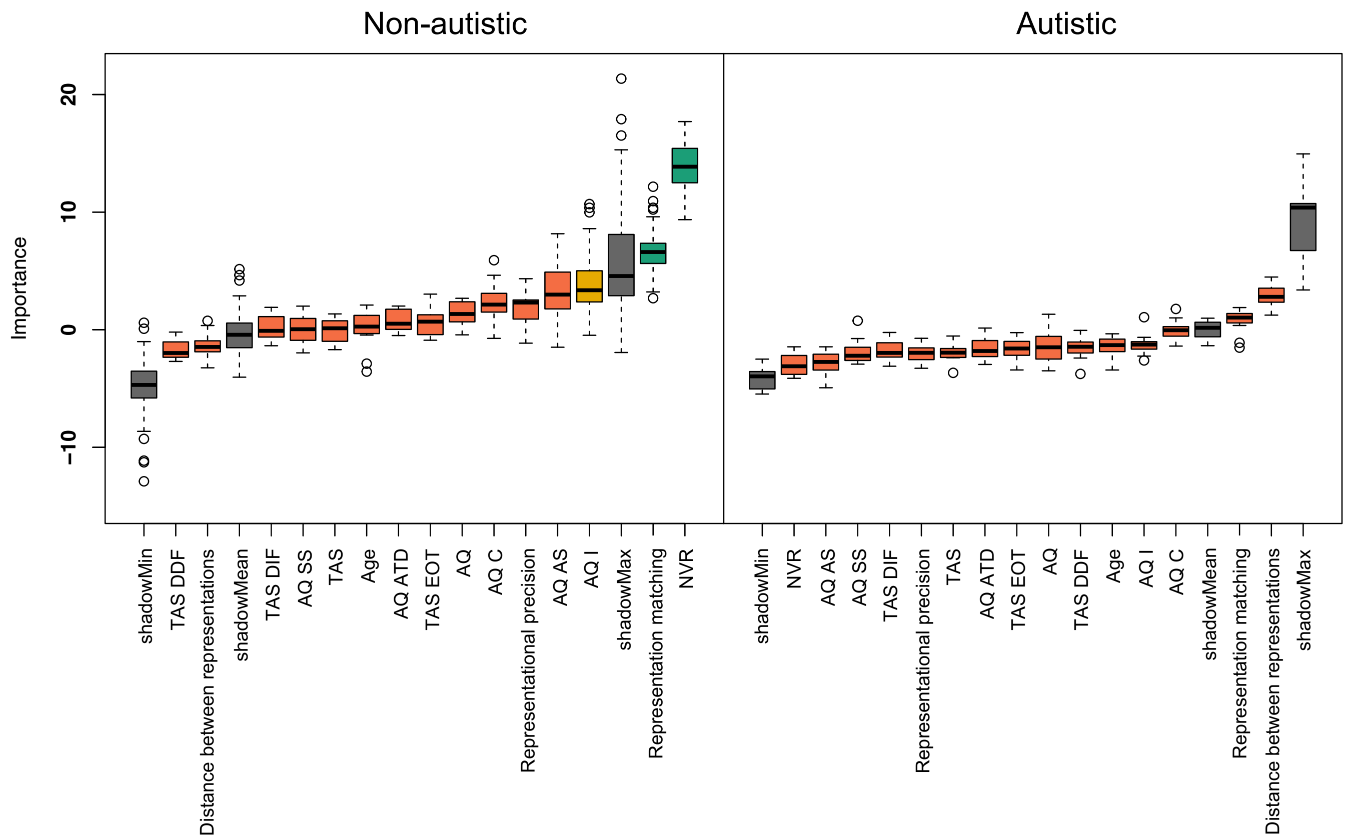
5.2.2. Determining the contributors to autistic and non-autistic emotion recognition

To determine the relative importance of our variables of interest for autistic and non-autistic emotion recognition, we conducted a random forests analysis[431] in each group using the *Boruta*[432] wrapper algorithm (version 7.7.0; as in [473]). Random forest regression is a supervised machine learning technique that constructs a large number of decision 'trees', each predicting a continuous outcome variable with a collection of factors, and then aggregates these predictions into one final result (by taking a mean of the predictions from the individual tress). The Boruta wrapper algorithm starts by randomly shuffling each predictor variable and adding these shuffled variables (termed "shadow features") to the dataset. Following this, across many iterations (here, 1500), the algorithm trains a random forest regression on all the predictors, as well as their shuffled copies (i.e., "shadow features"), and categorises a variable as *important* (i.e., useful for predicting a target variable) when its importance score is higher than the highest importance score for a shadow feature (termed "shadowMax" in the analysis; see [474] for an accessible summary of the Boruta wrapper algorithm). In this analysis, our outcome variable was mean accuracy and our predictor variables were total AQ score, total TAS score, the AQ and TAS subscales (i.e., AQ Social Skills, AQ Attention Switching, AQ Attention to Detail, AQ Communication, AQ Imagination, TAS Difficulties Describing Feelings, TAS Difficulties Identifying Feelings, and TAS Externally Oriented Thinking), non-verbal reasoning ability, age, mean representational precision, mean distance, and the interaction between representational precision and matching (‘representation matching’), (thus following similar procedures to [473]).

For non-autistic participants, of the 15 variables tested, two were confirmed *important*, one was tentative, and 12 were confirmed *unimportant.* Figure 5.1 (left) illustrates that the interaction between representational precision and matching and non-verbal reasoning were classed as important for non-autistic emotion recognition, with mean importance scores of 6.57 and 13.88 respectively. AQ Imagination score was classified as tentatively important with a mean importance score of 3.78. All other variables were deemed unimportant. In contrast, for autistic participants all 15 of the tested variables were confirmed *unimportant* (see Figure 5.1 right).

Figure 5.1.

Random forest variable importance scores for non-autistic (left) and autistic (right) participants.



Note. Variable importance scores for all 15 variables included in the Boruta random forest regression model, displayed as boxplots. Box edges correspond to the interquartile range (IQR); whiskers represent 1.5 × IQR distance from box edges; circles denote outliers. Box colour reflects the decision made by the algorithm: Green = confirmed important, yellow = tentative, red = rejected; grey = shadow features – shadowMin, shadowMean, shadowMax (minimum, mean and maximum variable importance scores of shadow features, respectively).

Following this, to verify the result from our random forests analysis for non-autistic individuals, we constructed a Bayesian linear regression model (using a default Jeffreys-Zellner-Siow prior; r scale = 0.354) of accuracy as a function of non-verbal reasoning, the interaction between representational precision and matching ('representation matching'), and

AQ Imagination score. The strongest model that emerged from this analysis included just non-verbal reasoning ability and the representational precision x matching interaction as predictors of emotion recognition accuracy (and not AQ I score) [BF_{10} = 149.64, R^2 = 33.5%]. According to the model, there was very strong evidence that both of these factors contribute to emotion recognition accuracy for non-autistic individuals. When this analysis was conducted with autistic participants, there was moderate evidence that these variables did not predict emotion recognition accuracy [i.e., the null hypothesis; BF_{10} = 0.15, R^2 = 1.00%], thus confirming the results from our previous analysis.

5.3. Discussion

The current study compared autistic and non-autistic adults on features of visual representations thought to be implicated in emotion recognition (e.g., precision and differentiation of visual emotion representations, general matching ability), and investigated the contribution of these factors to emotion recognition in both groups. We found that the autistic participants had more precise visual emotion representations (in the speed domain) across all three emotions, thus contradicting our expectations. In addition, we identified that there were no significant differences between groups in emotion recognition accuracy. This was true across all levels of the spatial and kinematic manipulations. This finding contradicts previous studies identifying group differences in emotion recognition (e.g., [191,385,475,476]) and instead supports literature suggesting emotion recognition performance is comparable between autistic and non-autistic people (e.g., [207,243,244,477,478]). Furthermore, there were no significant differences between groups in differentiation – as indexed by the distance between emotion representations - or matching ability. Hence, although autistic individuals may have less distinct emotional experiences (as in [148]), they have comparably distinct visual representations (at least in the speed domain) to their non-autistic counterparts. In sum, these results show that the autistic participants had more precise emotion representations (in terms of speed), but that this did not confer any benefit in terms of accuracy on our task which indexed emotion recognition from dynamic stimuli (although it is possible that having more precise visual emotion representations benefits autistic individuals on other types of tasks).

Here, it is important to consider alternative explanations for our conclusion that the autistic participants had more precise visual emotion representations (relative to their non-autistic peers). A primary question concerns whether the autistic participants achieved higher representational precision simply due to a focus on local details of the PLF expressions (i.e., a small number of points in the PLFs), thus facilitating more consistent speed attributions. Our findings suggest that this is unlikely: post-hoc correlations demonstrate moderate evidence [$r = -0.071$, $p = .509$, $BF_{10} = 0.181$] for a null relationship between representational precision and the attention to detail subscale of the AQ. Therefore, it is unlikely that the autistic participants had more precise visual emotion representations simply due to a focus on local details in our ExpressionMap paradigm. Another explanation is that the autistic individuals have lower cognitive flexibility, resulting in these individuals approaching each trial in a similar way each time, leading to more precise visual representations. Again, this explanation is not probable since there is moderate evidence [$r = 0.097$, $p = .364$, $BF_{10} = 0.152$] for a null relationship between representational precision and the attention switching subscale of the AQ (a proxy for cognitive flexibility). As such, it is not the case that the autistic participants exhibited greater representational precision due to a focus on local details or reduced cognitive flexibility. Rather, our results suggest that autistic individuals truly have more precise representations of facial expressions in their mind's eye (with respect to speed).

To determine the relative importance of various abilities (e.g., precision of representations, distance between representations, general matching ability) and clinically relevant individual differences (e.g., non-verbal reasoning, AQ, TAS) to autistic and non-autistic emotion recognition, we conducted random forest analyses employing the Boruta wrapper algorithm. Whilst for non-autistic individuals, non-verbal reasoning ability and the interaction between representational precision and matching were classified as *important*, and AQ Imagination score was classified as *tentatively important* for emotion recognition, no variables were deemed important for autistic emotion recognition. Of particular note, none of the variables corresponding to features of emotion representations contributed to autistic emotion recognition (i.e., precision of representations, distance between representations, the representational precision x matching interaction). That is, these factors were no better than randomly shuffled data at predicting emotion recognition accuracy. Thus, aside from precision (where autistic participants exhibited more precise emotion representations in terms of speed) there were minimal differences between the groups (matching, distinctness and accuracy did not significantly differ); nevertheless, there were differences in the way these variables were related such that autistic participants did not exhibit the predictive relationship between features of representations and emotion recognition accuracy that is exhibited by non-autistic people. These results suggest differences in the psychological mechanisms underpinning emotion recognition from dynamic stimuli in autism.

One possible mechanistic difference is that autistic individuals may not be ‘using’ their (precise) emotion representation (or ‘using’ them to a lesser extent) to help them recognise emotional expressions. This idea aligns well with Bayesian accounts of autism which posit that autistic individuals are less influenced by priors than non-autistic people (see [261]). To date, there is mixed evidence in relation to these Bayesian accounts, with some studies suggesting weaker prior influences, others suggesting no differences, and a handful suggesting larger prior influences in autism (see [479]). Furthermore, there is variance across domains: for 'social priors', the evidence is almost evenly split between suggesting weaker prior influences and no differences, while for simpler perceptual priors there are usually no differences between autistic and non-autistic people (see [479]). One issue that is unresolved in this field is the question of whether autistic individuals possess *weaker* priors and/or whether autistic individuals are *less influenced* by priors. The two are orthogonal to each other so that, in theory one could have strong priors but nevertheless be weakly influenced by them. Our results raise the hypothesis that - at least in the domain of emotion recognition – autistic individuals have strong priors (i.e., precise emotion representations in the speed domain) but are, nevertheless weakly influenced by them (i.e., the relationship between the priors and on emotion recognition accuracy is minimal). Future research is required to test this hypothesis.

If it is true that autistic individuals are less guided by their visual emotion representations, we might expect these individuals to perform better on tasks that do not require a comparison between incoming facial expressions and internal templates. For example, they may perform better on affect matching paradigms, wherein participants have to judge whether two expressions show the same or different emotions (i.e., differentiate emotional expressions that are presented to participants sequentially or simultaneously), rather than labelling paradigms, where participants may have to compare to their visual representations in order to produce the correct emotion label. In line with this, whilst numerous studies employing matching paradigms show comparable emotion recognition performance between autistic and non-autistic people (e.g., [243,480-482]), those employing labelling paradigms often document differences between these groups (e.g., [229,483-488]). As such, our findings may help disentangle mixed findings regarding emotion recognition in autism by suggesting that autistic individuals may have particular difficulties on tasks that mandate comparison to their internal templates.

If autistic individuals are less guided by their visual representations of emotion, how are they able to achieve high levels of accuracy on our emotion recognition task? One plausible explanation is that autistic individuals have developed compensatory strategies that allow them to achieve comparable accuracy to non-autistic participants on certain tasks (e.g., in the current study; see [216]). The nature of these compensatory strategies may vary from person to person, but one possibility is that autistic people use explicit cognitive or verbally mediated strategies to help them recognise emotions (in contrast to more automatic processing in non-autistic individuals[216,256,257]). Here, rather than automatically comparing their visual emotion representations to incoming facial expressions, the autistic participants may instead follow a "rule-based strategy" where they assess the degree to which the expression matches a list of features they have learnt to be associated with anger (e.g., "furrowed eye-brow", "fast-moving", etc.), happiness ("lip raising", "teeth showing", etc.), and sadness ("downturned mouth", "slow-moving", etc), along with other emotions[256,257].

If autistic participants are using an alternative, cognitive or verbal, strategy we might expect emotion recognition performance to be more related to general cognitive or verbal ability for autistic people than for non-autistic people. Supporting this idea, studies have found that mental age[215], and receptive and expressive language[258] predict emotion recognition ability in autistic, but not non-autistic, children. Concurrently, if autistic individuals are less reliant on visuo-spatial cues (such as visual emotion representations), we might also expect non-verbal reasoning ability to be less associated with emotion recognition performance in the autistic than non-autistic group. In line with this, here we found that non-verbal reasoning ability was a significantly stronger predictor of emotion recognition accuracy [$z = -2.251$, $p < .05$] for the non-autistic [$t = 3.88$, $p < .001$, $BF_{10} = 74.16$, $R^2 = 0.259$], than autistic [$t = -0.46$, $p = 0.650$, $BF_{10} = 0.321$, $R^2 = 0.005$], participants. Third, if it is true that autistic individuals employ more effortful cognitive/verbally mediated mechanisms to recognise emotions (rather than a more automatic processing style), this could explain why autistic individuals typically exhibit longer emotion recognition response latencies than non-autistic individuals (e.g., [229-238]; though note there could be other explanations for longer response latencies). Here, the PLF stimuli were presented for relatively long durations (approximately 6 seconds on average), thus providing the autistic participants sufficient time to employ their compensatory strategies (and hence they were able to reach comparable accuracy scores). Further research is necessary to confirm whether autistic individuals adopt a rule-based strategy to read emotional facial expressions.

Limitations

The results of the current study are informative with respect to understanding the emotion representations of autistic and non-autistic individuals from facial motion cues alone. However, since many features of expressions are involved in emotion processing, such as shading/depth[377] and pigmentation/colouring[376], one should be cautious to assume that our findings generalise to full dynamic emotional expressions (e.g., full video recordings of facial expressions). It could be, for instance, that the precision of emotion representations and matching ability are important for autistic emotion recognition for full dynamic expressions, but not point-light displays. However, since our study was motivated by the observation of group differences in emotion recognition[385], and links discovered between emotion representations and emotion recognition from facial motion cues alone (as in [469,473]), it was crucial to our overall research question that we used PLF stimuli in the current study. Although this was an active design choice, motivated by previous research demonstrating a causal role of speed cues in emotion recognition[239] and other *a priori* hypotheses (see [449]), in future work we will develop our paradigms to encompass other spatiotemporal emotion cues. Thus, facilitating comparisons of visual emotion representations between autistic and non-autistic individuals with respect to other cues such as the degree of spatial exaggeration, movement onset/offset, texture and colour.

It is also important to address the limitations of our study with respect to generalizability. Notably, the participants in our sample were predominantly white (86.67%; see Appendix 4.2), highly educated (see Appendix 4.3), English-speaking individuals from highly developed countries. As such, our sample may not be representative of those with lower levels of education or intellectual disabilities, or those from different racial, ethnic, cultural, or socioeconomic backgrounds. With respect to the former, whilst autistic individuals with average to high IQs often have comparable emotion recognition performance (e.g., [209,244,477,478]), those with co-occurring intellectual disabilities appear to struggle with emotion recognition (e.g., [215,489,490]), relative to IQ or mental age-matched comparison groups (though see [491]). Hence, we may not have found emotion recognition difficulties here due to our autistic participants possessing high levels of intelligence (as demonstrated by their high level of education). With respect to the latter, since the participants in our sample are predominantly from developed countries, where emotion recognition interventions are increasingly being offered to autistic individuals (e.g., [476,492,493]), it may be that some of our autistic participants have undergone training in the past, thus improving their emotion recognition scores. Hence, our findings may not represent the emotion recognition performance of autistic individuals from less developed countries. Future studies should aim to dismantle barriers to inclusion to boost the representativeness of their samples, thus allowing us to identify whether specific subgroups of autistic individuals (e.g., those with intellectual disabilities) have difficulties with emotion recognition (and other emotion processes).

Conclusion

The current study aimed to compare autistic and non-autistic participants on features of their emotion representations, and determine whether the same processes are implicated in autistic and non-autistic emotion recognition. Using a method of adjustment design, we found that autistic individuals had more precise visual emotion representations than their non-autistic counterparts (in the speed domain). That is, the autistic participants were more precise (i.e., consistent) in the speeds they attributed to angry, happy and sad facial expressions across repetitions. Nevertheless, this enhanced precision did not confer any benefit for their emotion recognition. Whilst for non-autistic people, non-verbal reasoning and the interaction between precision of emotion representations and matching ability predicted emotion recognition, no variables contributed to autistic emotion recognition. These findings highlight the possibility that autistic individuals are less guided by their emotion representations (a form of prior). Future research is necessary to identify what traits, processes, and strategies are implicated in autistic emotion recognition.

5.4. Method

This study was approved by the Science, Technology, Engineering and Mathematics (STEM) ethics committee at the University of Birmingham (ERN_16-0281AP9D) and was conducted in accordance with the principles of the revised Helsinki Declaration. Informed consent was obtained from all participants.

5.4.1. Participants

A total of 45 autistic and 45 non-autistic participants were recruited from the Birmingham Psychology Autism Research Team (B-PART) database, the Centre for Autism Research Oxford database, and Prolific. All participants in the ASD group had previously received a clinical diagnosis of ASD from an independent clinician. As expected, the participants in the ASD group had significantly higher AQ scores than those in the non-autistic group (see Table 5.1.).

The sample size was based on an a priori power analysis conducted using G*Power[402], which focuses on replicating the group-difference in recognition accuracy (between autistic and non-autistic individuals) for angry videos at the normal spatial and speed level[385]. Using data from Keating et al[385], 25 participants are required in each group in order to have 80% power to detect an effect size of 0.719 (Cohen's d) at alpha level 0.05 for this group-difference in accuracy. Since Button and colleagues[342] argue that sample size calculations are likely to be optimistic, we recruited 45 participants in each group in order to ensure we obtained adequate power.

Table 5.1.

Means, standard deviations, and group differences of participant characteristics. In the central columns, means are followed by standard deviation in parentheses.

Variable	ASD (n=45)	Non-ASD (n = 45)	Significance
Sex	30 Female, 14 Male, 1 Prefer not to say	26 Female, 19 Male	p = .360
Age	35.51 (14.06)	34.87(9.01)	p = .398
NVR	65.83%(15.31%)	63.70%(15.20%)	p = .255
AQ-50	37.31(7.64)	21.44(7.34)	p < .001
TAS-20	64.60(12.46)	57.49(11.99)	p = .004

Note. Age is in years.

5.4.2. Procedures

Following participatory research guidelines[318,319], prior to conducting this study, a group of individuals from the autism community (from the Birmingham Psychology Autism Research Team Consultancy Committee) provided feedback on our research (e.g., about task design and instructions, frequency of breaks, and suggested routes for dissemination, etc.). Following this consultation, we made a number of changes (e.g., added instruction videos for the ExpressionMap and Visual Matching task to promote understanding and accessibility) before starting to recruit participants.

Participants completed demographics questions, followed by the 50-item Autism Quotient[304] (as in Chapter 2), and the 20-item Toronto Alexithymia Scale[344] (as in Chapter 2). Following this, participants completed three tasks that employed dynamic point light displays (a series of dots that convey biological motion) of angry, happy and sad facial expressions (PLFs). Participants completed the ExpressionMap paradigm[473] (as in Chapter 4), followed by the Visual Matching task[473] (as in Chapter 4), followed by the PLF Emotion Recognition task (as in Chapter 2). Finally, participants completed the Matrix Reasoning Item Bank (MaRs-IB)[343] (as in Chapter 2). Within each task, participants were encouraged to take regular breaks in between blocks. All parts of the study were completed online in one sitting. Together, these questionnaires and tasks took approximately two hours and 30 minutes to complete.

5.4.3. Statistical analyses

All frequentist analyses were conducted using R Studio (version 2021.09.2) and all Bayesian analyses were conducted using JASP (version 0.16). For all frequentist analyses, we used a significance threshold of $p = 0.05$ to determine whether to accept or reject the null hypothesis. The frequentist approach was supplemented with the calculation of Bayes Factors, which quantify the relative evidence for one theory or model over another. For all Bayesian analyses, we followed the classification scheme used in JASP[352]: BF_{10} values between one and three reflect weak evidence, between 3 and 10 as moderate evidence, and greater than ten as strong evidence for the *experimental* hypothesis. Conversely, BF_{10} values between 1 and 1/3 reflect weak evidence, between 1/3 and 1/10 as moderate evidence, and smaller than 1/10 as strong evidence for the *null* hypothesis respectively[352].

Chapter 6: Similarities and differences in the psychological mechanisms involved in autistic and non-autistic emotion recognition

In Chapter 4, in addition to showing that the precision of visual representations contributes to emotion recognition, we also demonstrated that (for non-autistic people) the precision and differentiation of emotional *experiences* is linked to emotion recognition performance. Hence, our results reveal additional potential candidate mechanisms that may underpin the emotion recognition difficulties of autistic individuals: they may have less precise and/or less differentiated emotional experiences than their non-autistic counterparts, leading to challenges interpreting other people's emotions. This is particularly plausible given that previous studies have found autistic individuals have greater difficulties differentiating their own emotions than their non-autistic peers[148]. The following chapter tests this possibility, first by comparing the precision and differentiation of emotional experiences between groups after controlling for alexithymia, and second by examining the contribution of these factors to emotion recognition in each group, respectively.

Publication 5:

Similarities and differences in the psychological mechanisms involved in autistic and non-autistic emotion recognition

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(Published in PsyArXiv, under review)

Reference: Keating CT, Kraaijkamp C, Cook J. Similarities and differences in the psychological mechanisms involved in autistic and non-autistic emotion recognition.
https://doi.org/10.31234/osf.io/6deqs

Abstract

The extant literature hints at the idea that differences in the autistic population in the recognition of others' emotions might be related to differences in the way emotions are experienced. Specifically, autistic individuals may differ in the precision of emotional experiences, ability to differentiate between emotions, and/or semantic conceptions of emotions. Here, we empirically tested this claim by (1) investigating whether autistic and non-autistic adults differed in the precision and/or differentiation of their emotional experiences, and their understanding and differentiation of emotion concepts, after controlling for alexithymia, and (2) assessing the contribution of these emotional abilities to emotion recognition. Hence, 50 autistic and 50 non-autistic individuals, matched on age, sex, and non-verbal reasoning completed several computer-based tasks. We found no group differences in emotional precision, emotion differentiation, and the understanding or differentiation of emotion concepts after controlling for alexithymia. For both groups, the ability to differentiate one's own emotions contributed to enhanced emotion recognition. Whilst having more differentiated emotion concepts contributed to elevated emotion recognition for non-autistic people, having a more precise understanding of emotion concepts contributed for autistic people. These findings highlight similarities and differences in the mechanisms involved in autistic and non-autistic emotion recognition.

6.1. Introduction

Autism spectrum disorder (hereafter 'autism') is a neurodevelopmental condition, characterised by restricted and repetitive interests and difficulties with social communication and interaction[151]. Although not considered a diagnostic feature, emotion recognition has been a topic of interest in autism research for over three decades because it is thought that difficulties in this area may contribute to social challenges (e.g., [215]). To date, the majority of emotion recognition research has aimed to determine whether differences exist between autistic and non-autistic individuals (see [146,191,216]). This literature is famously mixed (see [146,218] for reviews): some studies show differences in emotion recognition between groups, while others find no differences, or emotion-specific difficulties (for example in recognising angry expressions[147,191,219-222,385]). Here, instead of focusing on assessing whether there are group differences in emotion recognition, we explore whether there are differences in the *way in which* autistic people read emotional expressions. That is, we ask whether autistic and non-autistic people typically employ different *mechanisms* to recognise the emotions of others.

One potential candidate mechanism concerns the way in which autistic and non-autistic people use their *experiences* of their own emotions when recognising others' emotions. A person's internal emotional landscape is an important contributor to how well they can recognise the emotions of others (see [473]). For instance, individuals who have more *precise* and *differentiated* emotional experiences typically find it easier to successfully recognise other people's emotions. Our previous work provided empirical support for this in a large (N = 193) sample of non-autistic participants[473]. Participants completed a two-part "EmoMap" paradigm wherein they first viewed pairs of images each known to selectively induce either anger, happiness or sadness[430], and rated how similar the evoked emotions felt. They subsequently selected the image that made them feel the most angry, happy, or sad. Emotion differentiation was calculated using a multidimensional scaling algorithm to transform similarity scores into 'distances' between emotions. Emotional precision was calculated based on the logical consistency of participants' responses: if a participant selected image A over image B, and image B over image C, but then selected image C over image A, this would comprise an inconsistent decision and would indicate imprecision in their emotional experience. Thus, individuals with highly precise and differentiated emotions are precise in their emotional responses to the images and feel very different inside when they experience anger, happiness and sadness. Previously we found that (non-autistic) participants with more precise and differentiated emotional experiences typically had greater emotion recognition accuracy on an independent test[473]. At present, it is not known whether the same is true for autistic individuals.

Another potential contributing factor to emotion recognition concerns how well individuals understand semantic emotion concepts (i.e., the semantic meaning associated with the emotion) and are able to differentiate these from one another (e.g., differentiating the concept of sadness from disappointment). Contemporary theories of emotion and emerging evidence suggest that semantic emotion concepts shape how individuals "construct" both emotional experiences (i.e., inferences about how oneself is feeling) and emotion perceptions (i.e., inferences about how others are feeling)[51-56]. Specifically, these theories suggest that from childhood through adulthood, emotion concepts evolve from a "positive vs. negative" dichotomy into increasingly differentiated multidimensional representations, producing concomitant shifts in the experience and perception of emotion[51]. That is, possessing emotion concepts that are differentiated across more dimensions will encourage individuals to differentiate between their own affective experiences, and others' emotional facial expressions, across more dimensions (e.g., arousal and context in addition to valence). Hence, as we develop, we move away from conceptualizing, experiencing and perceiving, emotions as "good" and “bad”, to conceptualizing, experiencing, and perceiving them more precisely (e.g., based on arousal, context, etc.).

Although theories to date are highly informative, they have not yet specified whether emotion concepts influence experiences and perceptions independently and directly, or whether there are indirect effects amongst these variables (one variable influences another, which influences a third variable). It could be, for example, that having precise and distinct semantic emotion concepts helps an individual to differentiate between their own emotional states, which in turn helps them to tell apart others’ emotional expressions. To determine the mechanistic pathways amongst these variables, studies employing causal manipulation are necessary. However, at present, the putative direction of causality is unknown, thus making it impossible to determine which factor should be the target for manipulation. Here, research employing mediation analyses offer a potential solution, identifying the most mathematically pathways, and thus opening avenues to future studies formally testing the degree of causality and directionality between these variables.

Preliminary work suggests that there may be differences between autistic and non-autistic people in their ability to differentiate experiences and semantic concepts of emotion. Erbas and colleagues[148], for example, have argued that autistic adults have less differentiated experiences and concepts of emotion than their non-autistic counterparts. In support of this, Erbas and colleagues found that the autistic participants sorted emotion terms into fewer conceptual groupings, suggesting these individuals make less fine-grained distinctions between emotion concepts. Autistic adults also had less differentiated emotional responses to emotion-inducing images[148]. Importantly, however, this study did not control for alexithymia - a subclinical condition, highly prevalent in autistic people[199], characterised by difficulties identifying and describing one’s own emotions[194]. This could be problematic as it is thought that autistic individuals' challenges with emotion-processing (including emotion differentiation) may be underpinned by alexithymia, and not autism (see [207]). Further research is necessary to understand whether autistic people have less differentiated experiences and concepts of emotion after controlling for alexithymia.

Although research has demonstrated a role for both emotion differentiation *and* emotional precision in the recognition of emotion[473], studies have not yet examined emotional precision in the context of autism. However, it could be that emotional precision is lower in autism (in addition to emotion differentiation as described above), thus contributing to emotion recognition difficulties. Alternatively, given that different traits and processes appear to be involved in autistic and non-autistic emotion recognition[147,246,426], this factor may not contribute to emotion recognition for autistic individuals at all.

In sum, it is unclear whether there are differences between autistic and non-autistic individuals in emotional precision, and/or in the differentiation of experiences and semantic concepts of emotion, after controlling for alexithymia. Such differences could conceivably feed into challenges with recognising other's emotional expressions. As such, the current study had two primary aims: (1) to investigate whether autistic and non-autistic adults differed in the precision and/or differentiation of their experiences and semantic conceptions of emotion, and (2), to assess whether differences therein were related to individual differences in emotion recognition. Additionally, in order to identify putative mechanistic pathways, we conducted exploratory post-hoc analyses to identify whether the ability to differentiate one's own emotions mediates the relationship between the differentiation of emotion concepts and emotion recognition. Importantly, throughout, we control for alexithymia to ensure that any differences between the groups arise due to autism, and not alexithymia, as has been found in previous work[207,209,212,213].

6.2. Method

This study was approved by the Science, Technology, Engineering and Mathematics (STEM) ethics committee at the University of Birmingham (ERN_16-0281AP9D) and conducted in line with the principles of the revised Helsinki Declaration.

6.2.1. Participants

58 autistic and 59 non-autistic participants were recruited from the Birmingham Psychology Autism Research Team (B-PART) database, the University of Birmingham Research Participation Scheme, and Prolific. All participants in the ASD group had previously received a clinical diagnosis of ASD from an independent clinician. As expected, the autistic participants had significantly higher Autism Quotient (AQ)[304] scores than the non-autistic participants [$U = 384.5$, $Z = -7.24$, $p < .0001$]. We employed a 2 standard deviation cutoff for identifying and excluding outliers as recommended by Berger and Kiefer[494], due its low absolute bias (i.e., low risk of type-I and type-II errors[494]). That is, we excluded participants with AQ scores that were over 2 standard deviations higher or lower than their group mean, and those with performance on the emotion-based tasks over 2 standard deviations worse than their group means since it is likely that such low performance levels are due to attentional lapses and not representative of true ability. Reassuringly we observed that many of the excluded participants also failed multiple attention checks and that the exclusion of participants did not affect the results of the group comparisons on our main measures (i.e., no significant group differences were found in emotional precision, the differentiation of experiences and concepts of emotion, or understanding of emotion concepts regardless of whether these participants were included or excluded). After the exclusions, our final sample comprised 50 autistic and 50 non-autistic participants that were matched on age, sex, and non-verbal reasoning ability (see Table 6.1.). The ethnicities of these participants are reported in Appendix 5.1.

Table 6.1.

Means, standard deviations, and group differences of participant characteristics. In the central columns, means are followed by standard deviation in parentheses.

Variable	Non-autistic (n=50)	Autistic (n = 50)	Significance
Sex	30 Female, 20 Male	26 Female, 22 Male, 2 Prefer not to say	p = .304
Age	31.64 (15.08)	32.42 (10.42)	p = .382
NVR	58.83% (13.81%)	61.80% (18.49%)	p = .183
AQ-50	20.04 (7.53)	36.66 (5.51)	p < .001
TAS-20	47.62 (13.20)	62.66 (10.11)	p < .001

Note. Age is in years.

The chosen sample size was based on an a priori power analysis conducted using G*Power[402]. To have 80% power to detect emotion differentiation as a significant predictor of emotion recognition accuracy (effect size $f^2 = 0.159$), at alpha level 0.05, 41 participants in each group are required. However, since Button and colleagues[342] argue that sample size calculations are likely to be optimistic, we ensured that we had at least 50 participants in each group.

6.2.2. Procedures

Following participatory research guidelines[318,319] prior to conducting the study, members of the autism community (from the Birmingham Psychology Autism Research Team Consultancy Committee) provided feedback on our research (e.g., on task design and instructions, suggested dissemination routes, etc.). Following this consultation, we made several changes before starting data collection.

Participants provided informed consent and then completed demographics questions, the Autism Quotient[304], and the Toronto Alexithymia Scale[344] on Qualtrics (see Chapter 2 for a description of these questionnaires). Following this, participants completed EmoMap[473] (see Chapter 4), the Point Light Face (PLF) Emotion Recognition Task[239] (see Chapter 2), the emotional vocabulary test (inspired by Nook et al[51]) and the Matrix Reasoning Item Bank[343] (see Chapter 2) on Gorilla.sc. All parts of the study were completed online.

6.2.3. Materials and Stimuli

EmoMap

A full description of our EmoMap paradigm can be found in Chapter 4. An advantage of this paradigm is that it allows us to measure emotion differentiation without requiring participants to translate their emotional experiences into words, unlike existing tasks (see [450] for a full discussion). This is particularly beneficial for the current study as autistic individuals sometimes have different language and communication profiles to non-autistic individuals (see [495,496]). Removing the requirement to translate their emotional experiences into words means that our task focuses on participants' ability to differentiate their *emotional signals*, rather than their ability to produce emotion labels.

Emotional Vocabulary Test

We assessed participants' semantic conceptions of 20 different emotions (i.e., *affection, amusement, anger, anxiety, awe, contentment, depression, desire, disgust, embarrassment, excitement, fear, guilt, happiness, interest, irritation, loneliness, peaceful, sadness, surprise*) using an adapted version of the emotional vocabulary test (from [51,497]). The list of emotions was selected to include a) the six basic emotions[498], b) emotions that occupy all four quadrants of the circumplex dimensions of arousal and valence[41], and c) emotions that are most frequently evoked by standardised databases of images (e.g., the Nencki Affective Picture System, the International Affective Picture System)[499]. In this task, on each trial, participants were required to type a definition of an emotion word that was presented on screen. In order to ensure data validity, we i) explicitly instructed participants to come up with definitions themselves (rather than searching for them online), ii) forced the task into full-screen so that we could tell if participants minimised the page to look-up definitions, and iii) excluded any definitions that matched those provided by the Oxford, Cambridge, and Meriam Webster dictionaries.

In the current study, we consider how well participants understand the meaning (i.e., the semantic content) of emotion concepts, and how these meanings overlap between emotions. To this end, we calculated two types of scores using the definitions provided by participants - emotional vocabulary test scores, which pertain to the accuracy of participants' definitions, and conceptual distance scores, which reflect the conceptual overlap in participants' own definitions. To calculate emotional vocabulary scores, first, a trained experimenter assigned each definition a score of zero, one, or two (as in a WASI vocabulary test and in Nook et al[51]). A score of two was awarded if the participants provided i) a plausible and specific definition of the emotion, ii) a direct synonym of the emotion, or iii) a scenario that would conceivably evoke the given emotion and not other emotions. We assembled a list of definitions and synonyms (taken from the Oxford and Cambridge Dictionaries and from Nook et al[51]) which the experimenter referred to when scoring the responses. A score of one was awarded if the participant provided a definition that was of the correct valence or situation, but too vague to meet criteria for a two-point response. For example, if a participant defined loneliness as "the feeling of being alone", or "a sad feeling", they would score one point for this definition. To score two points, participants would need to include both parts of this definition: e.g., "the sad feeling you get when you are alone". A score of 0 was awarded if the participants gave definitions, synonyms, or situations relevant to a different emotion. We calculated total emotional vocabulary scores by summing the scores for each item. As such, emotional vocabulary test scores ranged from 0 to 40, with higher scores representing more accurate understanding of emotion terms.

To calculate conceptual distance scores, we employed Natural Language Processing – a machine learning technique facilitating the analysis and synthesis of large quantities of language data[500]. Specifically, we used a pre-existing model (*sentence-transformers/all-mpnet-base-v2*) designed to analyse the meaning of sentences, and then compute the conceptual similarity of sentence pairs (i.e., the similarity in meaning of sentence pairs). During its development, this model was trained on one billion sentence pairs, derived from numerous online sources, thus enhancing the reliability of the conceptual similarity estimates. In the current study, we used this model to compute conceptual similarity scores for each pair of definitions (e.g., Affection-Amusement, Affection-Anger, Affection-Anxiety…. Sadness-Surprise), which we then inverted (by multiplying by -1) to get conceptual distance scores. These conceptual distance scores range from 0 to -1 (to 15 decimal places), with higher scores representing greater differentiation of semantic emotion concepts. To assess the differentiation of participants' conceptions of same-valence emotions (within valence conceptual distance), we took a mean of the conceptual distance scores for the 45 positive-positive definition pairs (e.g., Affection-Amusement, Affection-Happiness, etc.), and 45 negative-negative definition pairs (e.g., Anger-Anxiety, Anger-Sadness, etc.), and then averaged across these values. To assess the differentiation of participants' conceptions of opposite-valence emotions (between valence conceptual distance), we took a mean of the conceptual distance scores for the 100 positive-negative definition pairs.

Logically, if our task and analysis pipeline are operating as intended, between valence conceptual distance scores should be higher (i.e., more positive) than within valence conceptual distance scores. In order to verify this, we conducted a paired samples t-test on these data, identifying *extreme* evidence [$BF_{10} > 100$] that between valence conceptual distance [mean(SEM) = -0.28(0.006)] was higher than within valence conceptual distance [mean(SEM)

= -0.40(0.008); $t(99) = 32.55$, $p < .0001$, $BF_{10} = 1.34e^{51}$]. Encouragingly, we also identified that the five lowest mean conceptual distance scores were for the Anxiety and Fear [mean(SEM) = -0.59(0.015)], Depression and Sadness [mean(SEM) = -0.58(0.017)], Contentment and Peaceful [mean(SEM) = -0.56(0.020)], Contentment and Happiness [mean(SEM) = -0.55(0.019)], and Anger and Irritation [mean(SEM) = -0.54(0.018)] definition pairs, as one would expect (as these concepts are close to one another in meaning).

In addition, we calculated the mean number of words included across all definitions for each participant. We included this in our analyses to ensure that emotional vocabulary score, between valence conceptual distance, and within valence conceptual distance were significant predictors after controlling for the length of definition (i.e., to ensure it is not just the case that some individuals wrote shorter definitions and so had more/less overlap in conceptions).

6.2.4. Statistical analyses

All frequentist analyses were conducted using *R Studio* (version 2021.09.2) and all Bayesian analyses were conducted using *JASP* (version 0.16). For all frequentist analyses, we used a significance threshold of $p = 0.05$ (two-sided) to determine whether to accept or reject the null hypothesis. Parametric assumptions were met for all analyses employing simple linear models and linear mixed effects models. Non-parametric linear regressions were conducted when assumptions were violated. We conducted all linear mixed effects models in R Studio using the lmer function (from the *lme4* package). In addition, we employed the Anova function (from the *car* package) to conduct a Type III ANOVA on the results of our linear mixed model with a Kenward-Roger[470] approximation for degrees of freedom, as supported by Luke[471]. In R Studio, we also conducted i) a random forest analysis[431] employing the Boruta wrapper algorithm (Boruta function from *Boruta* package)[432], and ii) mediation analyses using the sem() function (from the *lavaan* package). We conducted Bayesian analyses in JASP in order to determine the relative strength of evidence for the experimental versus null hypotheses. For all Bayesian analyses, we followed the classification scheme proposed by Lee and Wagenmakers[352]: BF_{10} and BF_{01} values between one and three reflect weak evidence, between 3 and 10 reflect moderate evidence, greater than 10 reflect strong evidence, and greater than 100 reflect extreme evidence for the *experimental* (BF_{10}) and *null* (BF_{01}) hypotheses, respectively.

6.3. Results

In the following section, we (1) compare autistic and non-autistic participants on the precision and differentiation of emotional experiences, understanding of emotion concepts, and differentiation of emotion concepts, and (2) determine whether the same processes are implicated in autistic and non-autistic emotion recognition.

6.3.1. Analyses comparing autistic and non-autistic participants

No differences between groups in emotional precision

First, to compare the precision of emotional experiences (as measured by the EmoMap task) between participant groups, we conducted a linear mixed effects model with emotional precision as the dependent variable, emotion (angry, happy, sad), group (autistic, non-autistic), the interaction between emotion and group [independent variables], age, sex, non-verbal reasoning ability, alexithymia, emotional vocabulary score, between valence conceptual distance, within valence conceptual distance, and mean definition word count [control variables] as predictors, and subject number as a random intercept. This revealed that within valence conceptual distance was a positive predictor of emotional precision [$F(1,89) = 9.67$, $p = .003$, $\eta_p^2 = 0.03$, 95% Confidence Intervals(CI) = (3.60, 15.86)]: those with more differentiated conceptions of same-valence emotions typically had greater emotional precision.

Most notably, however, there was no main effect of group [$F(1,263.54) = 0.08$, $p = .784$, $\eta_p^2 = 0.00$, 95%CI = (-11.05, 8.34)], no emotion x group interaction [$F(2,196) = 0.99$, $p = .373$, $\eta_p^2 = 0.00$], nor any other significant predictors [all $p > .05$]. Hence, to probe the strength of the evidence supporting the idea that there were no differences in emotional precision between groups, we employed a post-hoc Bayesian ANOVA. This analysis provided moderate evidence that there was no main effect of group [$BF_{01} = 4.13$] or an emotion x group interaction [$BF_{01} = 6.16$]. Using a default prior (Uniform prior), there was moderate evidence for excluding the main effect of group [$BF_{exclusion} = 6.03$], and strong evidence for excluding the emotion x group interaction [$BF_{exclusion} = 14.33$] (relative to including these variables) when attempting the explain the data. These results generalized well across priors for both the main effect of group [Beta binomial: $BF_{exclusion} = 7.67$; Wilson: $BF_{exclusion} = 4.99$] and the emotion x group interaction [Beta binomial: $BF_{exclusion} = 15.68$; Wilson: $BF_{exclusion} = 17.04$]. Together, this evidence suggests that there were no differences between the autistic and non-autistic participants in emotional precision.

No differences between groups in emotion differentiation for distinct emotional states

To test whether autistic adults have less differentiated experiences of distinct emotions than non-autistic adults, we constructed a linear mixed effects model with distance between clusters as the dependent variable, emotion pair (angry-happy, angry-sad, happy-sad), group (autistic, non-autistic), the interaction between emotion pair and group [independent variables], age, sex, non-verbal reasoning, alexithymia, emotional vocabulary score, between valence conceptual distance, within valence conceptual distance, and mean definition word count [control variables] as predictors. In line with the results from our previous study[473], there was a significant main effect of emotion pair [$F(2,196) = 89.98$ $p < .001$, $\eta_p^2 = 0.60$]: the distance between angry and sad clusters was smallest [mean(SEM) = 13.87(0.26)], followed by happy and sad [mean(SEM) = 18.05(0.44)], followed by angry and happy [mean(SEM) = 18.93(0.43)]. In addition, between valence conceptual distance was also a significant positive predictor of distance between clusters [$F(1,89) = 4.95$, $p = .029$, $\eta_p^2 = 0.05$, 95%CI = (0.20, 3.16)]: those with less differentiated *conceptions* of emotions (of opposite valence) typically had less differentiated *experiences* of distinct emotions. Finally, our analysis also revealed that non-verbal reasoning ability was a significant negative predictor of distance between clusters [$F(1,89) = -4.23$, $p = .043$, $\eta_p^2 = 0.05$, 95%CI = (-1.37, -0.03)]: those with poorer non-verbal reasoning ability typically had greater distances between clusters. Once again there was no main effect of group [$F(1,124.52) = 1.69$, $p = .196$, $\eta_p^2 = 0.01$, 95%CI = (-2.95, 0.60)] nor an interaction between emotion pair and group [$F(2,196) = 1.94$, $p = .146$, $\eta_p^2 = 0.02$], nor any other significant predictors of distance between clusters [all $p > .05$]. To assess the strength of the evidence suggesting no differences in distance between clusters for autistic compared to non-autistic individuals, we employed a post-hoc Bayesian ANOVA. This analysis provided anecdotal evidence that there was no main effect of group [$BF_{01} = 1.26$], and moderate evidence that there was no emotion x group interaction [$BF_{01} = 3.02$]. Using a default prior (Uniform prior), there was anecdotal evidence for excluding the main effect of group [$BF_{exclusion} = 1.08$], and the emotion x group interaction [$BF_{exclusion} = 1.48$] (relative to including these variables) when attempting the explain the data. These results generalized to some extent across priors: notably the strength of the evidence remained anecdotal, however, for some priors the evidence was in favour of a main effect of group [Beta binomial: $BF_{exclusion} = 0.60$; Wilson: $BF_{exclusion} = 0.48$] and an emotion x group interaction [Beta binomial: $BF_{exclusion} = 0.99$; Wilson: $BF_{exclusion} = 0.59$]. In sum, here we found no credible evidence for a difference between the autistic and non-autistic participants in the differentiation of distinct emotional states.

No differences between groups in emotion differentiation for similar emotional states

Next, to test whether autistic adults have less differentiated experiences of similar emotions (i.e., less granular emotional experiences), we constructed a linear mixed effects model with distance within clusters as the dependent variable, emotion (distance within angry, happy, and sad clusters respectively), group (autistic, non-autistic), the interaction between emotion and group [independent variables], age, sex, non-verbal reasoning, alexithymia, emotional vocabulary score, between valence conceptual distance, within valence conceptual distance, and mean definition word count [control variables] as predictors, and subject number as a random intercept. This revealed a main effect of emotion [$F(2,196) = 14.38$, $p < .001$, $\eta_p^2 = 0.20$]: distance within happy clusters was lowest [mean(SEM) = 12.41(0.25)], followed by distance within angry clusters [mean(SEM) = 13.69(0.25)] and distance within sad clusters [mean(SEM) = 13.73(0.25)]. In addition, our analysis identified that between valence conceptual distance [$F(1,89) = 6.48$, $p = .013$, $\eta_p^2 = 0.07$, 95%CI = (0.28, 2.12)] was a significant positive predictor of distance within clusters: those with less differentiated conceptions of emotions (of opposite valence) typically had less differentiated experiences of similar emotions. We also identified that non-verbal reasoning was a significant negative predictor of distance within clusters [$F(1, 89) = -11.23$, $p = .001$, $\eta_p^2 = 0.11$, 95%CI = (-1.14, -0.30)]. There was no main effect of group [$F(1,148.43) = 0.43$, $p = .514$, $\eta_p^2 = 0.02$, 95%CI = (-1.35, 0.67)], nor an emotion x group interaction [$F(2,196) = 1.14$, $p = .321$, $\eta_p^2 = 0.01$], and there were no other significant predictors of distance within clusters [all $p > .05$]. Hence, to probe the strength of the evidence supporting the idea that there were no differences in the distance within clusters between groups, we employed a post-hoc Bayesian ANOVA. This analysis provided anecdotal evidence that there was no main effect of group [$BF_{01} = 2.52$] and moderate evidence that there was no emotion x group interaction [$BF_{01} = 5.85$]. Using a default prior (Uniform prior), there was anecdotal-moderate evidence for excluding the main effect of group [$BF_{exclusion}$ = 2.97] and the emotion x group interaction [$BF_{exclusion}$ = 4.85] (relative to including these variables) when attempting the explain the data. These results generalized well across priors for both the main effect of group [Beta binomial: $BF_{exclusion}$ = 1.92; Wilson: $BF_{exclusion}$ = 1.32] and the emotion x group interaction [Beta binomial: $BF_{exclusion}$ = 3.24; Wilson: $BF_{exclusion}$ = 2.20]. Together, this evidence suggests that there were no differences between the autistic and non-autistic participants in the distance within emotion clusters.

No differences between groups in levels of understanding of emotion concepts

To assess the understanding of emotion concepts, we compared the emotional vocabulary test scores of the autistic and non-autistic participants. To do so, we ran a non-parametric multiple regression of emotional vocabulary as a function of group (autistic, non-autistic), age, sex, non-verbal reasoning, alexithymia, and mean definition word count [control variables]. This analysis revealed that mean definition word count [$t(92) = 3.56$, $p < .001$, 95%CI = (0.11, 0.39)] predicted emotional vocabulary score: those who provided longer definitions typically had higher emotional vocabulary scores. There were no significant differences between the autistic participants and non-autistic participants in emotional vocabulary score [$t(92) = -1.95$, $p = .055$, 95%CI(-5.79, 0.06)]. A follow-up Bayesian independent sample t-test, using a default prior (Cauchy width = 0.707) revealed anecdotal evidence for this null effect [BF_{01} = 1.04, 95%CI = (-0.04, 0.72)], which generalized well across both wide [BF_{10} = 1.31, 95%CI = (-0.03, 0.74)] and ultrawide [BF_{01} = 1.73, 95%CI = (-0.03, 0.75)] priors. Thus, although we found no significant differences between groups in the understanding of emotion concepts using frequentist statistics, there is only anecdotal evidence that there are no differences between groups based on a Bayesian approach.

No differences between groups in the extent of overlap in semantic conceptions of emotion

Following this, to determine whether autistic or non-autistic people have more differentiated conceptions of emotions with the same and opposite valences, we constructed two simple linear models as a function of group (autistic, non-autistic), age, sex, non-verbal reasoning, alexithymia, and mean definition word count [control variables]. For both models, the only significant predictor was mean definition word count [between valence: $F(1,92) = -7.84$, $p = .006$, $\eta_p^2 = 0.08$, 95%CI = (-0.03, -0.00); within valence: $F(1,92) = -8.60$, $p = .004$, $\eta_p^2 = 0.09$, 95%CI = (-0.04, -0.01)]: those who provided longer definitions tended to have lower conceptual distance scores, both for same-valence and opposite-valence emotions. There was no effect of group [between valence conceptual distance: $F(1,92) = 3.33$, $p = .071$, $\eta_p^2 = 0.03$, 95%5CI = (-0.00, 0.07); within valence conceptual distance: $F(1,92) = 1.12$, $p = .293$, $\eta_p^2 = 0.02$, 955%CI = (-0.01, 0.04)], nor any other significant predictors in both models [all $p > .05$]. Follow-up Bayesian independent sample t-tests, using a default prior (Cauchy width = 0.707), provided moderate evidence that there was a null effect of group for both between valence conceptual distance [$BF_{01} = 4.70$, 95%CI = (-0.40, 0.34)] and within valence conceptual distance [$BF_{01} = 3.46$, 95%CI = (-0.52, 0.22)]. These results generalized well across priors: there was moderate evidence for the null hypothesis for both wide [between valence conceptual distance: $BF_{01} = 6.43$, 95%CI = (-0.35, 0.41); within valence conceptual distance: $BF_{01} = 4.66$, 95%CI = (-0.22, 0.54)] and ultrawide [between valence conceptual distance: $BF_{01} = 8.94$, 95%CI = (-0.36, 0.41); within valence conceptual distance: $BF_{01} = 6.40$, 95%CI = (-0.22, 0.55)] priors. Together, this evidence suggests that there were no differences between autistic and non-autistic participants in the extent of overlap in semantic conceptions of emotion.

In sum, we found no credible evidence for differences between autistic and non-autistic individuals in emotional precision, the differentiation of emotional experiences, or the understanding and differentiation of semantic emotion concepts, after controlling for alexithymia.

6.3.2. Different combinations of variables are important for autistic and non-autistic emotion recognition

Next, we aimed to determine the factors that contribute to autistic and non-autistic emotion recognition respectively. Thus, we ran a random forests analysis[431] in each group using the *Boruta*[432] wrapper algorithm (as described in [426,473]; see Chapter 5). In this analysis, our outcome variable was mean emotion recognition accuracy. We included the emotion-related variables studied here as predictors: emotional precision, distance between clusters, distance within clusters, emotional vocabulary score, between valence conceptual distance and within valence conceptual distance. For exploratory purposes, we also included total AQ score, total TAS score, the AQ and TAS subscales[d] (i.e., AQ Social Skills, AQ Attention Switching, AQ Attention to Detail, AQ Communication, AQ Imagination, TAS Difficulties Describing Feelings, TAS Difficulties Identifying Feelings, and TAS Externally Oriented Thinking), non-verbal reasoning ability, and age as predictors (thus following similar procedures to [425,473]), since these variables are also thought to be involved in emotion-processing (e.g., [146,207,385,473]).

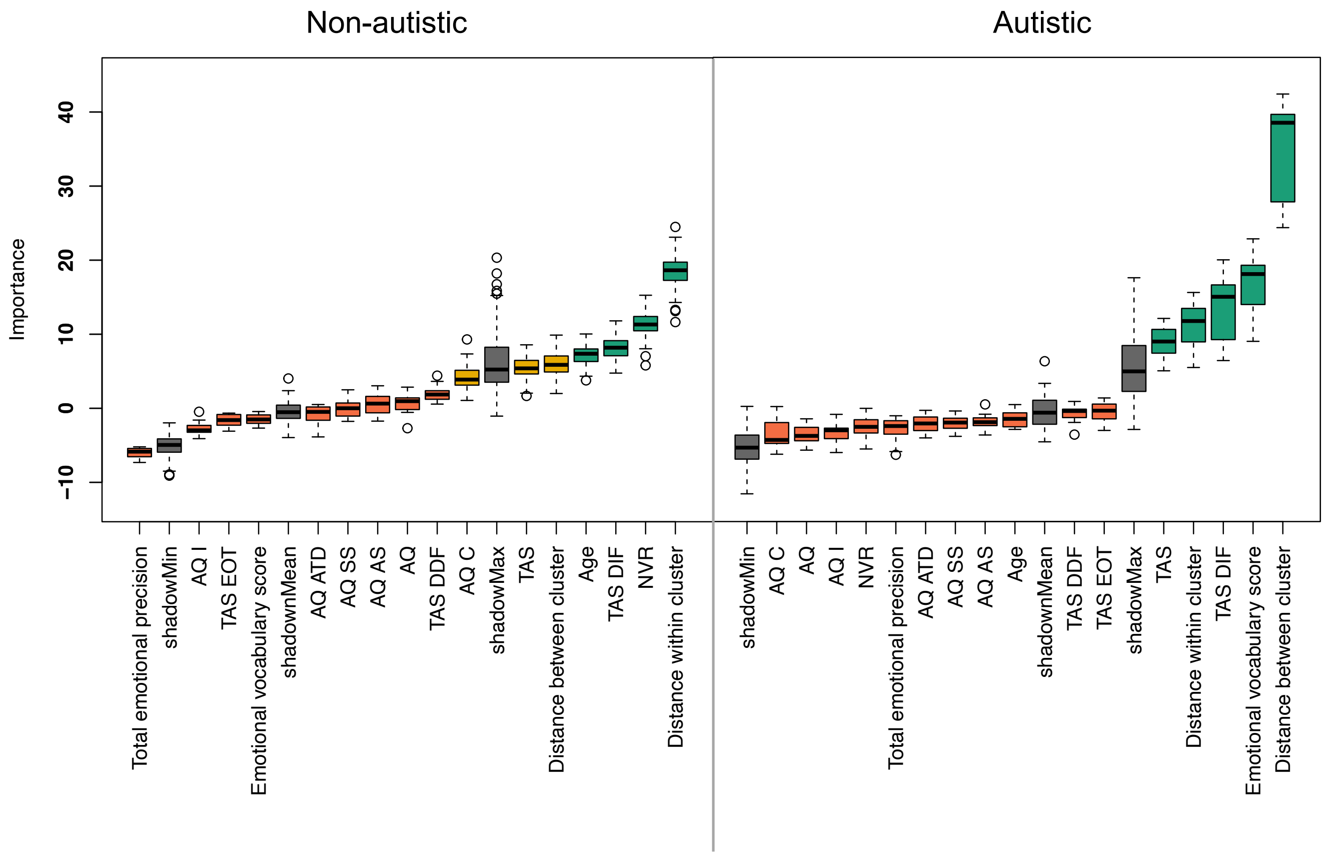
For the non-autistic participants, of the 18 variables tested, four were classified as important, three were classified as tentatively important, and 11 were deemed unimportant. Figure 6.1 (left) illustrates that the distance within clusters [mean importance score; MIS = 18.57], non-verbal reasoning ability [MIS = 11.34], the TAS difficulty identifying feelings (TAS DIF) subscale [MIS = 7.87] and age [MIS = 7.44] were important for emotion recognition; distance between clusters [MIS = 5.87], total TAS score [MIS = 5.17], and the AQ

[d] Since random forests analyses are less affected by issues of multi-collinearity, we were able to include all of the AQ and TAS subscale, which are highly correlated with one another, in this analysis.

communication subscale [MIS = 4.00] were tentatively important for emotion recognition. All other variables were deemed unimportant. In comparison, for the autistic participants, six of the variables were classified as important and the remainder were classed as unimportant for emotion recognition. Figure 6.1 (right) shows that the distance between emotion clusters [MIS = 33.69], emotional vocabulary score [13.43], the TAS difficulty identifying feelings subscale [12.59], distance within emotion clusters [10.56], between valence conceptual distance [MIS = 7.72] and total TAS score [7.71] were all classed as important for autistic emotion recognition.

Figure 6.1.

Random forest variable importance scores for non-autistic (left) and autistic (right) participants.



Note. Variable importance scores for all 18 variables included in the Boruta random forest regression model, displayed as boxplots. Box edges correspond to the interquartile range (IQR); whiskers represent 1.5 × IQR distance from box edges; circles denote outliers. Box colour reflects the decision made by the algorithm: Green = confirmed important, yellow = tentative, red = rejected; grey = shadow features – shadowMin, shadowMean, shadowMax (minimum, mean and maximum variable importance scores of shadow features, respectively).

Next, to verify the results from our random forests regression model, we constructed linear mixed effects models predicting mean emotion recognition accuracy with the important and tentatively important variables in the autistic and non-autistic groups respectively. Since we identified a strong correlation between two variables of interest - distance between emotion clusters and distance within clusters [$R = .746$, $p < .001$, 95%CI = (0.59, 0.85), $R^2 = 55.65\%$] – we constructed two linear mixed effects models with near identical predictors but where one model included distance *between* emotion clusters and the other included distance *within* clusters. Thus, ensuring that parameter estimates were not compromised by collinearity issues. In the model that excluded distance *between* clusters, distance within clusters [$F(1,43) = 15.99$, $p < .001$, $\eta_p^2 = 0.27$, 95%CI = (0.23, 0.67)], non-verbal reasoning [$F(1,43) = 13.55$, $p < .001$, $\eta_p^2 = 0.24$, 95%CI = (0.19, 0.63)] and AQ communication score [$F(1,43) = -8.58$, $p = .005$, $\eta_p^2 = 0.17$, 95%CI = (-0.57, -0.11)] were significant predictors of non-autistic emotion recognition. In the model that excluded distance *within* clusters, distance between clusters [$F(1,43) = 4.53$, $p = .039$, $\eta_p^2 = 0.10$, 95%CI = (0.02, 0.49)], non-verbal reasoning ability [$F(1,43) = 6.09$, $p = .018$, $\eta_p^2 = 0.12$, 95%CI = (0.06, 0.53)], and AQ communication score [$F(1,43) = 5.99$, $p = .019$, $\eta_p^2 = 0.12$, 95%CI = (-0.58, -0.06)] were significant predictors of non-autistic emotion recognition. Therefore, both distance between clusters and distance within clusters predict emotion recognition performance for non-autistic people.

Following this, we constructed the relevant linear mixed effects models in the autistic group. In the model that excluded distance *between* clusters, distance within clusters [$F(1,44) = 13.10$, $p < .001$, $\eta_p^2 = 0.23$, 95%CI = (0.21, 0.71)], emotional vocabulary score [$F(1,44) = 15.98$, $p < .001$, $\eta_p^2 = 0.27$, 95%CI = (0.28, 0.83)], and TAS DIF [$F(1,44) = 8.07$, $p = .007$, $\eta_p^2 = 0.15$, 95%CI = (0.19, 1.04)], predicted emotion recognition performance. Similarly, in the model that excluded distance *within* clusters, distance between clusters [$F(1,44) = 22.27$, $p <$

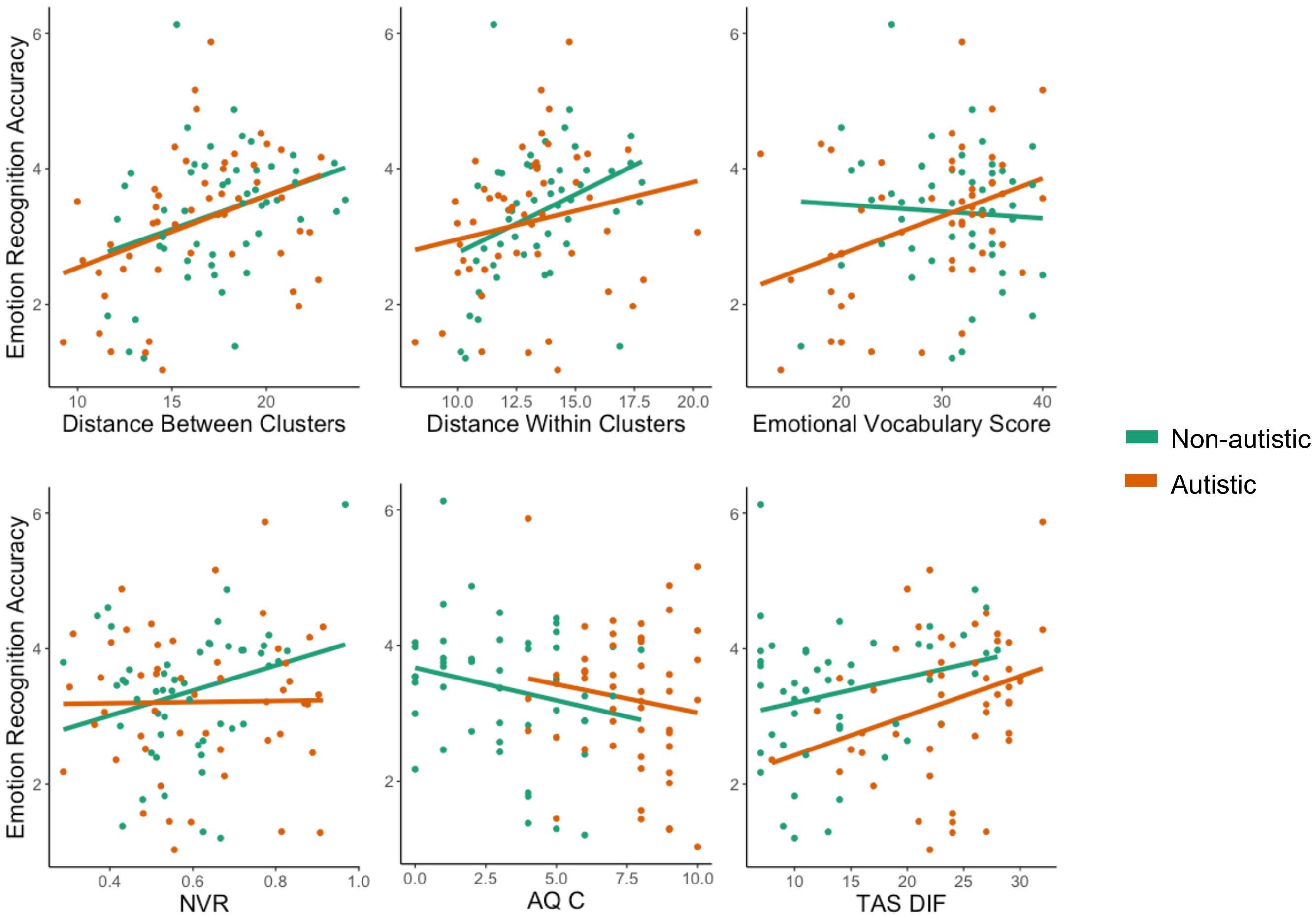
.001, $\eta_p^2 = 0.34$, 95%CI = (0.31, 0.76)], emotional vocabulary score [$F(1,44) = 15.01$, $p < .001$, $\eta_p^2 = 0.25$, 95%CI = (0.24, 0.73)], and TAS DIF score [$F(1,44) = 7.04$, $p = .011$, $\eta_p^2 = 0.14$, 95%CI = (0.14, 0.92)] predicted emotion recognition accuracy. Thus, - just as we saw for non-autistic participants - both distance between clusters and distance within clusters predict emotion recognition performance for autistic people.

To determine the strength of evidence for these predictive models we constructed two Bayesian linear regressions predicting emotion recognition accuracy in each group using the variables found to be significant contributors above. For non-autistic participants, distance between clusters, distance within clusters, non-verbal reasoning ability, and AQ communication score accounted for 36.8% of the variance in emotion recognition accuracy. There was *extreme* evidence [$BF_{10} > 100$] that this model was a better fit to the data than a null model [$BF_{10} = 102.40$, $R^2 = 36.8\%$]. In contrast, for the autistic participants, distance between clusters, distance within clusters, TAS difficulties identifying feelings, and emotional vocabulary score together accounted for 51.2% of the variance in emotion recognition accuracy. Again, there was *extreme* evidence that this model was a better fit to the data than a null model [$BF_{10} = 16{,}125.73$, $R^2 = 51.2\%$].

In sum, distance between clusters and distance within clusters (i.e., the ability to differentiate between similar and distinct emotional states) predicted emotion recognition in both groups. However, whilst having enhanced non-verbal reasoning and communication (as shown by low scores on AQ Communication scale) contributed to elevated emotion recognition for non-autistic people this was not the case for the autistic group. For autistic individuals, having a more accurate understanding of emotion concepts and greater difficulties identifying one's own emotions (as shown by the difficulty identifying feeling subscale of the TAS), predicted elevated emotion recognition (see Figure 6.2).

Figure 6.2.

The relationships between mean emotion recognition accuracy and distance between clusters, distance within clusters, emotional vocabulary score, non-verbal reasoning ability (NVR), AQ Communication score (AQ C), and TAS Difficulty Identifying Feelings score (TAS DIF), respectively, for the autistic (orange) and non-autistic (green) participants.



6.3.3. Exploratory analyses: Emotion differentiation mediates the relationship between the differentiation of semantic emotion concepts and emotion recognition for non-autistic people

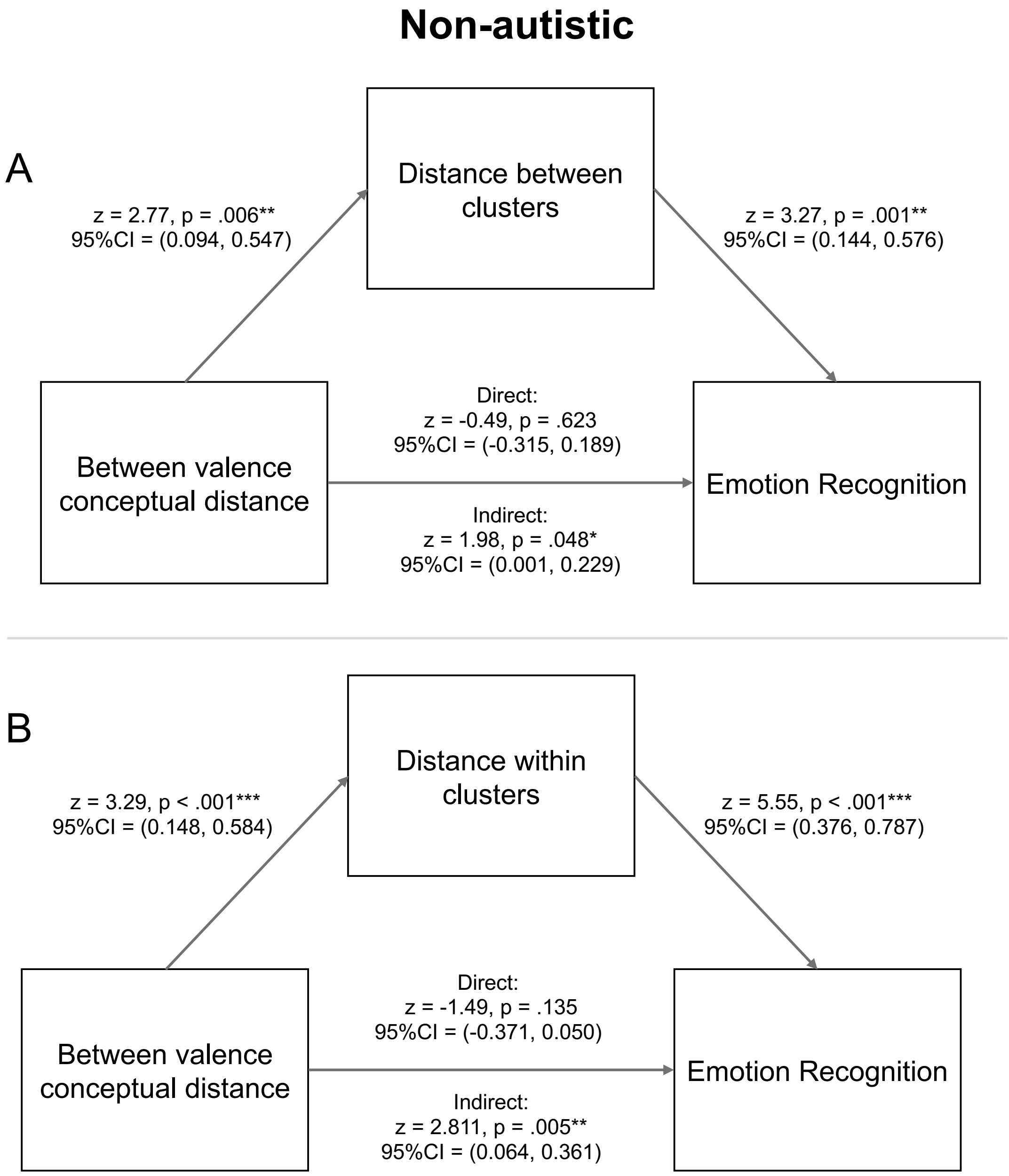
Since we had identified that between valence conceptual distance predicted distance between and within clusters, which both predicted emotion recognition performance, we conducted post-hoc mediation analyses to explore whether between valence conceptual distance exerted an indirect effect on emotion recognition by influencing the distances between and within clusters, in each group respectively. In the first model, the predictor was between valence conceptual distance, the mediator was distance *between* clusters, and the outcome variable was emotion recognition accuracy. In the second model, the predictor was between valence conceptual distance, the mediator was distance *within* clusters, and the outcome variable was emotion recognition. Across all mediation models we controlled for relevant confounding variables (non-verbal reasoning, AQ, TAS, emotional vocabulary score, mean definition word count) to enhance the internal validity of our findings.

First, we conducted these mediation analyses in the non-autistic group. For these participants, in the first model, whilst there was no direct effect [$z = -0.49$, $p = .623$, 95%CI = (-0.315, 0.189)] of between valence conceptual distance on emotion recognition, there was an indirect effect via distance between clusters [$z = 1.98$, $p = .048$, 95% CI = (0.001, 0.229); see Figure 6.3(A)]. This suggests a potential causal direction (though future studies are necessary to confirm this chain of causality); having well-differentiated emotion concepts may lead to individuals having well-differentiated experiences of distinct emotions, and then in turn greater emotion recognition accuracy. Similarly, in the second model, there was no direct effect of between valence conceptual distance on emotion recognition [$z = -1.49$, $p = .135$, 95% CI = (-0.371, 0.050)], but there was an indirect via distance within clusters [$z = 2.81$, $p = .005$ 95% CI = (0.064. 0.361); see Figure 6.3(B)]. As such, for non-autistic participants, having well-differentiated emotion concepts may also lead to them having well-differentiated experiences of more similar emotions, and then in turn greater emotion recognition accuracy. Future studies employing causal manipulation are needed to confirm this chain of causality.

To verify that these pathways were most plausible, we then swapped the position of distance between clusters and between valence conceptual distance, such that distance between clusters was the predictor and between-valence conceptual distance was the mediator. Our analysis revealed that the indirect effect was not significant [$z = -0.47$, $p = .638$, 95% CI = (-0.088, 0.054)]. Following this, we conducted the same analysis with distance within clusters, identifying once again that the indirect effect was not significant [$z = -1.28$, $p = .199$, 95% CI (-0.137, 0.029)]. Therefore, our results suggest that the most mathematically plausible pathway is as follows: having well differentiated semantic concepts of emotion may lead to more differentiated experiences of emotion, and then in turn better emotion recognition.

Figure 6.3.

Mediation models showing the contribution of between valence conceptual distance to non-autistic emotion recognition via distance between clusters (panel A) and distance within clusters (panel B), after controlling for non-verbal reasoning AQ, TAS, emotional vocabulary score, and mean definition word count.

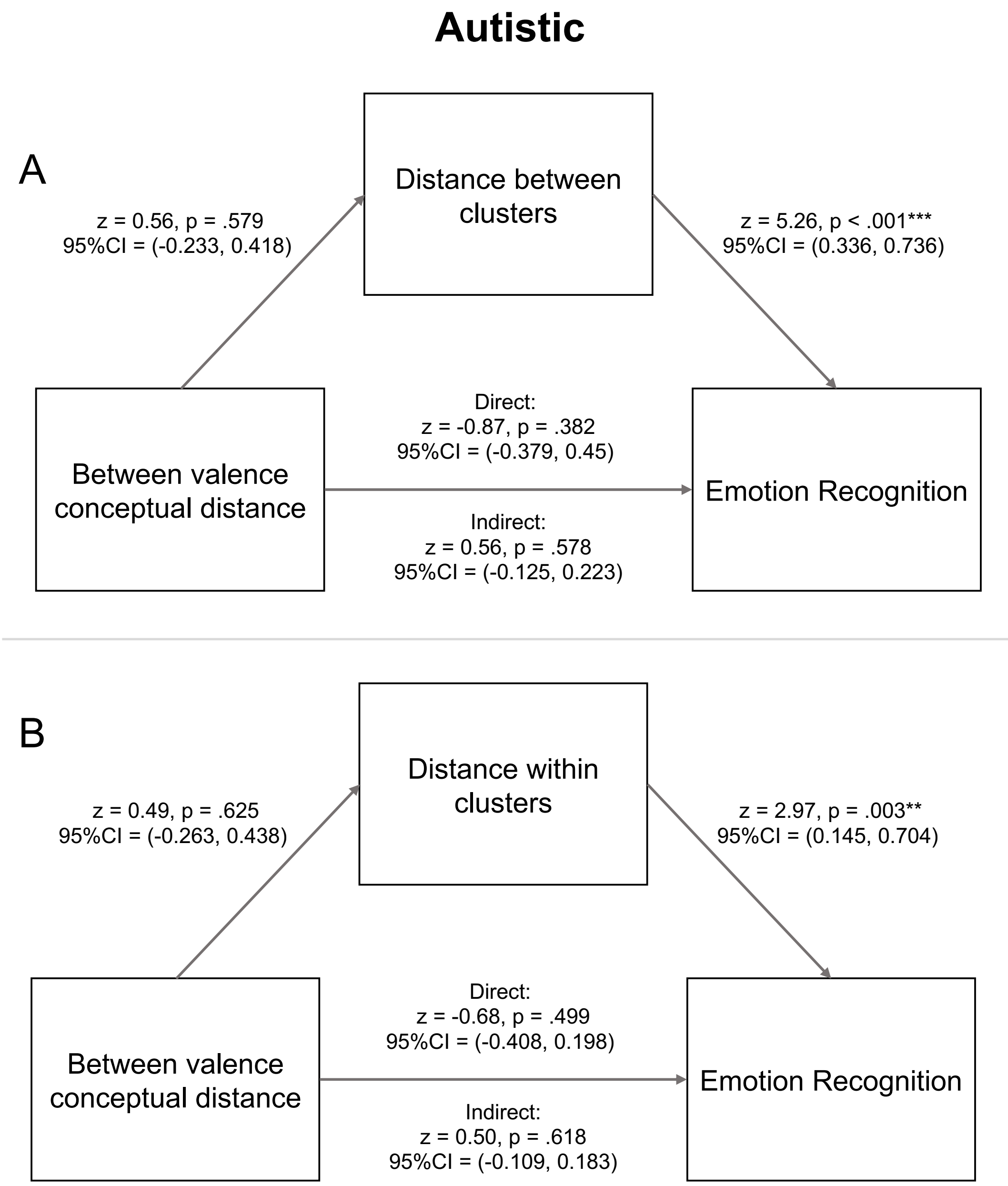


Note. The asterisks (*) denote statistical significance: *p<.05, **p<.01, ***p<.001.

Second, we completed these mediation analyses in the autistic group. This identified that, for the autistic participants, in the first model there was neither a direct effect [z = -0.87, p = .382, 95% CI = (-0.379, 0.145)] nor an indirect effect [z = 0.56, p = .578, 95% CI = (-0.125, 0.223); see Figure 6.4(A)] of between valence conceptual distance on emotion recognition performance via distance between clusters. Notably, between conceptual distance also did not predict distance between clusters in the autistic group [z = 0.56, p = .579, 95% CI = (-0.233, 0.418)]. Similarly, in the second model, there was no direct effect [z = -0.68, p = .499, 95% CI = (-0.408, 0.198)] or indirect effect [z = 0.50, p = .618, 95% CI = (-0.109, 0.183); see Figure 6.4(B)] of between valence conceptual distance on emotion recognition performance via distance within clusters. In addition, between valence conceptual distance did not predict distance within clusters in the autistic group [z = 0.49, p = .625, 95% CI = (-0.263, 0.438)]. Therefore, for autistic participants, the differentiation of emotion *concepts*, did not contribute to the differentiation of their emotional *experiences*, nor their emotion recognition performance (after controlling for these relevant characteristics).

Figure 6.4.

Mediation models showing the contribution of between valence conceptual distance to autistic emotion recognition via distance between clusters (panel A) and distance within clusters (panel B), after controlling for non-verbal reasoning, AQ, TAS, emotional vocabulary score, and mean definition word count.



Note. The asterisks (*) denote statistical significance: *p<.05, **p<.01, ***p<.001.

6.4. Discussion

The current study compared autistic and non-autistic adults on emotional abilities thought to be involved in emotion recognition (e.g., emotional precision, differentiation of experiences and concepts of emotion, and understanding of emotion concepts), and investigated the contribution of these factors to emotion recognition in both groups. Our results suggest that there are no differences between autistic and non-autistic people with respect to the precision and differentiation of emotional experiences, nor the understanding or differentiation of semantic concepts of emotion. However, notably, we identified similarities and differences in the traits, processes, and abilities involved in autistic and non-autistic emotion recognition. For both groups, individuals who had more differentiated experiences of distinct (e.g., angry-happy, angry-sad, happy-sad) and similar (e.g., anger, irritation, frustration) emotions also had a better ability to read others' emotional facial expressions as depicted in point light displays. However, whilst having higher non-verbal reasoning, enhanced communication (as indexed by low scores on the AQ Communication subscale), and more differentiated emotion concepts contributed to elevated emotion recognition accuracy for non-autistic individuals, the same could not be said for their autistic counterparts. Rather, for these individuals, having a more precise understanding of emotion concepts (as indexed by more accurate and precise definitions of emotion terms), and (surprisingly) greater difficulties identifying their own emotions, predicted enhanced emotion recognition performance.

These findings significantly advance our understanding of the processes and abilities involved in both autistic and non-autistic emotion recognition. To the best of our knowledge, no studies to date have empirically tested the mechanistic pathway by which emotion concepts influence emotion recognition. As discussed in the Introduction, one possibility is that emotion concepts impact upon emotional experiences and emotion perceptions directly and independently; another possibility is that there are indirect effects amongst these variables. This study suggests that the latter is more mathematically plausible; having well-differentiated *concepts* of emotion *may* lead to (non-autistic) individuals having well-differentiated *experiences* of emotion, and then in turn greater emotion recognition accuracy. This chain of causality raises a hypothetical pathway by which these abilities develop from infancy to adulthood (i.e., emotion concepts become increasingly differentiated, leading to increasingly differentiated emotional experiences, and then in turn emotion perceptions). Nevertheless, further research employing causal manipulation and/or longitudinal methods are necessary to verify this chain of causality, and to test how and when these links arise developmentally.

Similarly, these findings also significantly advance our understanding of the traits, processes, and abilities involved in autistic emotion recognition. Until now, the factors involved in autistic emotion recognition have remained elusive, with several studies finding that certain demographic factors, abilities, or processes important for non-autistic emotion recognition, are not important for autistic emotion recognition (e.g., no effect of age[246]; no same group advantage for emotion recognition[147]; no effect of the precision of visual representations[426]). Here we found that autistic individuals with more differentiated experiences of distinct and similar emotions, better understanding of emotional vocabulary and greater difficulties identifying their own feelings had better emotion recognition performance. This latter finding is particularly surprising as we would typically expect the opposite; individuals with greater difficulties identifying their emotions would typically be expected to exhibit *poorer* emotion recognition (in line with the alexithymia hypothesis[207]). One potential (post-hoc) explanation for this unexpected finding is that these individuals were aware that they have greater difficulties with emotions, and therefore tried harder on the emotion recognition task to compensate for this difficulty, leading to enhanced performance. This effect may be particularly dramatic in the autistic group as studies have shown that autistic individuals tend to underestimate their emotional abilities to a larger degree than their non-autistic counterparts[292]. Future studies should aim to test whether effort is mediating the effect of the TAS DIF subscale on emotion recognition performance.

The results of the current study contradict previous findings suggesting that autistic individuals have less differentiated experiences and concepts of emotions[148]. There are numerous potential explanations for this discrepancy. First, in the analyses conducted here, we have controlled for alexithymia – an important confounding variable that was not controlled for in previous studies. Hence, it is possible that the autistic participants tested previously had less differentiated experiences and concepts of emotion due to co-occurring alexithymia, rather than due to autism itself, in line with the alexithymia hypothesis (see [207]). Secondly, it could be the case that autistic individuals have particular difficulties on emotion differentiation tasks that require them to translate their emotional experiences into words (e.g., the photo emotion differentiation task in Erbas et al[148]), but do not exhibit differences with respect to tasks that purely focus on differentiating emotional signals (such as our EmoMap task). Nevertheless, although this is a possibility, if this were the case, we would have expected our autistic participants to perform more poorly than their non-autistic counterparts on the emotional vocabulary test (which they did not). Third, this discrepancy in findings could arise due to differences in demographics. Whilst the sample in the current study comprised 50 autistic and 50 non-autistic *adults* (with a mean age in each group of 32.42 and 31.64 years respectively), previous studies have tested younger samples (e.g., Erbas et al[148] tested 18 autistic and 26 non-autistic *adolescents* with a mean age of 16.71 and 16.56 years respectively). As such, it is possible that autistic individuals have particular difficulties differentiating experiences and concepts of emotions relative to their non-autistic peers during adolescence, which disappear as they transition into adulthood. Further research is necessary to a) replicate the results of the current study, and b) formally test under what conditions and tasks (e.g., age, language-based tasks) autistic people exhibit difficulties with emotion differentiation.

Implications

The results of the current study pave the way for future supportive interventions to help *both* autistic and non-autistic people to accurately recognise emotional facial expressions. Although we found no group differences, there is substantial variation in emotion recognition performance in both groups (scores ranging from 1.03 to 6.13). In this sample, 20% of participants exhibited low emotion recognition accuracy (scoring less than 2.5/10); these individuals tended to struggle to differentiate the emotional expressions, for example attributing high happy and sad ratings to angry expressions. Notably, this study illuminates emotion differentiation as a candidate mechanism that could be supported in order to improve the emotion recognition performance of these individuals. Such interventions have the potential to elicit broad benefits - enhanced emotion differentiation is not only associated with accurate emotion recognition, but also with adaptive emotion regulation, improved psychosocial functioning, and decreased mental health difficulties (see [293,439,501-505] for reviews). These interventions could be subtly adapted to emphasise improving the differentiation of emotion concepts (i.e., by focusing on the specific differences between the semantics of individual emotions) for non-autistic people, and the general understanding of emotion concepts for autistic people. Indeed, recent work employed a five-day intervention which aimed to increase conceptual emotion knowledge by providing detailed information about each emotion concept to participants, and then requiring them to compare these concepts to one another (thus targeting both general understanding of emotions and the differentiation of emotion concepts)[506]. This intervention had promising effects, successfully improving conceptual emotion knowledge and downstream emotion differentiation performance, relative to an active control group, immediately after training and at follow-up a month later[506]. Further research is necessary to assess whether such interventions have longer term benefits for conceptual emotion knowledge and emotion differentiation, and to determine whether these interventions have downstream benefits for autistic and non-autistic emotion recognition.

Chapter 7: Comparing the spatiotemporal and kinematic properties of autistic and non-autistic facial expressions

Thus far, we have examined whether there are differences between autistic and non-autistic individuals with respect to the conceptualisation, experience, and visual representation of emotion after controlling for alexithymia, and assessed whether differences therein contribute to emotion recognition. In the following chapter, we pose a similar question, examining whether there are differences in the facial expressions *produced* by these groups, and assess the extent to which participants' own productions contribute to their ability to recognise others' emotions. In doing so, we address the limitations of previous research (see section 1.4.5.) by employing methods with high sensitivity (i.e., facial motion capture) to compare the spatiotemporal and kinematic properties of autistic and non-autistic expressions, after controlling for facial morphology and alexithymia.

Publication 6:

Comparing the spatiotemporal and kinematic properties of autistic and non-autistic facial expressions

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(Published in *PsyArXiv,* under review)

Reference: Keating CT, Sowden, S, O'Donoghue, H, Cook J. Comparing the spatiotemporal and kinematic properties of autistic and non-autistic facial expressions.
https://doi.org/10.31234/osf.io/qapfs

Abstract

Preliminary studies are suggestive of differences in facial expressions between autistic and non-autistic individuals. However, it is unclear what specifically is different, whether such differences remain after controlling for facial morphology and alexithymia, and whether production differences relate to perception differences. Here we 1) compared jerkiness and activation profiles for autistic and non-autistic expressions, after controlling for morphology and alexithymia, and 2) explored whether differences therein predicted differences in emotion recognition. We employed facial motion capture techniques to record 2,448 posed and 2,448 spoken expressions of anger, happiness and sadness from 25 autistic and 26 matched non-autistic adults. Participants also completed a task assessing the ability to recognise emotions from dynamic stimuli. Autistic participants relied more on the mouth region to signal anger, whereas non-autistic individuals used both mouth and eyebrow cues; for happiness, autistic participants showed activity patterns suggestive of a less exaggerated smile that also did not "reach the eyes"; for sadness, autistic participants tended to make a downturned expression by raising their upper lip more than their non-autistic peers. Alexithymia predicted less differentiated angry and happy expressions, and less precision (reduced consistency) for spoken expressions. For non-autistic individuals, those who produced precise spoken expressions typically had greater emotion recognition accuracy. No production-related factors contributed to autistic emotion recognition.

7.1. Introduction

Emotion recognition challenges in the autistic population are a topic of ongoing debate. Autism spectrum disorder (hereafter 'autism') is a neurodevelopmental condition, characterised by difficulties with social communication and interaction[151]. While not regarded a diagnostic feature, emotion recognition has been a focus of autism research for over three decades because it is thought that challenges in this area may contribute to putative social difficulties[215]. Thus far, the majority of this literature has aimed to determine whether there are *differences* between autistic and non-autistic individuals in the ability to recognise the emotions of others (see [146]). This work has yielded mixed findings (see [146,216,217] for reviews): while some studies find differences in emotion recognition between groups, others find no differences, or emotion-, task-, or stimuli-specific differences (e.g., in recognising angry expressions[147,219-222,385]). Here, we focus on an under-explored area of research: emotion recognition is strongly influenced by the way in which a person uses their own body to express emotion. Here we build on this evidence base to first ask whether autistic people move their faces in a different way (compared to non-autistic people) when expressing emotions; second, we question whether the production of one's own facial expressions relates to the recognition of others'.

A burgeoning body of research suggests that the way we move our own bodies affects the way we label others' body movements. For example, leveraging evidence that fast movements tend to indicate anger and slow movements indicate sadness (e.g., [507-511]), Edey and colleagues[354] showed that people who typically walk fast tend to perceive others' fast movements as less intensely angry compared to people who typically walk slow; presumably because for fast walkers high speed movement looks relatively 'normal'. Conversely, slow movers perceived fast movements as appearing intensely angry[354]. That is, Edey and colleagues[354] showed that people use their own typical walking speed as a benchmark against which to judge the movements of others. Thus, production and perception are linked: one's own movements influence the interpretation of the movements of others.

A breadth of evidence suggests that autistic individuals tend to move their bodies in different ways from non-autistic individuals and that production differences might be linked to perception differences. Autistic individuals typically exhibit more jerky whole-body[512], upper limb[387,513-515], and head[516] movements (see [353]). Furthermore, Cook and colleagues[387] showed that within an autistic sample more jerky movements were correlated with differences in the perception of biological motion. Autistic individuals who moved in a particularly jerky fashion were less likely to view smooth, minimally jerky, animations as "natural". Thus, with respect to bodily movement, production differences have been linked to perception differences in the autistic population.

Preliminary evidence suggests that there are differences in the facial expressions produced by autistic and non-autistic people (see [146,150] for reviews). The majority of this evidence comes from studies where non-autistic observers, blind to diagnostic status, make ratings about the accuracy, quality, general appearance, and/or intensity of autistic and non-autistic facial expressions. Autistic expressions are generally perceived to be less accurate (i.e., less socially congruous), lower in quality, and 'atypical' in appearance (see [146,150]), being rated as odd, awkward or mechanical by (non-autistic) observers[263,265,266,278]. Some studies have also obtained 'intensity' ratings, though findings are mixed with some reporting more intense (e.g., [265-267]), and some less (e.g., [263,268-270]) autistic expressions. These studies - in which non-autistic observers subjectively rate expressions - suggest that there is something different about facial expressions produced by autistic and non-autistic people. If this is indeed the case, then perception differences might be linked to differences in the production of emotional facial expressions.

A handful of studies have employed more objective measures to attempt to quantify the way in which facial expressions produced by autistic and non-autistic people differ, however, a clear picture has not emerged. The evidence from studies using facial electromyography (fEMG) contradicts that from subjective ratings, suggesting that there are no differences between groups in expressivity[274,517]. Notably, this lack of an effect could arise due to fEMG not being sensitive to differences in the activation of facial muscles: fEMG is typically limited to studying just two muscle groups – one responsible for frowning (the corrugator supercili) and one responsible for smiling (the zygomaticus major)[277]. Nevertheless, other research employing fEMG suggests that autistic children typically display less differentiated facial muscle activation for positive and negative[518] and happy, angry, and fearful[273] facial expressions than their non-autistic peers. Such findings suggest that autistic individuals produce more overlapping facial expressions across different emotions.

An important consideration concerns facial morphology. In recent years, several studies suggest that there may be differences in facial morphology between autistic and non-autistic individuals (e.g., [279-282]). Thus, it could be that differences in the subjective appearance of expressions reflect differences in overall facial morphology (the shape and structure of the face) rather than differences in facial movement *per se*. Such differences in facial morphology may underpin subjective ratings of autistic expressions as odd or exaggerated[263,265-267,278], because the appearance of different features contributes to judgements of facial expressions (e.g., intensity judgements; see [519]). Thus, any studies comparing autistic and non-autistic facial expressions should thus aim to minimise the confounding influence of morphological differences.

A further issue is that many of these studies have used posed expressions that are not accompanied by other naturalistic forms of movement, such as speech. In everyday life, we produce emotional facial expressions *both* in isolation (without other concurrent movements, e.g., smiling when a friend announces good news), and while carrying out other movements like talking (e.g., smiling while verbally congratulating a friend). Arguably, studying the sorts of dynamic expressions that are produced during emotional verbalisations provides insight into the natural dynamics of emotional expression and is less affected by caricatured concepts relating to how expressions "should" appear. However, thus far, much of the literature has solely focused on comparing 'isolated' posed expressions that are free from other kinds of movements. Therefore, it is unclear whether there are differences in the facial expressions produced by autistic and non-autistic individuals when also carrying out other naturalistic movements (e.g., speech).

A third issue is that alexithymia has not been accounted for in the majority of previous research. Alexithymia comprises a subclinical condition, highly prevalent in the autistic population[199], that is characterised by difficulties identifying, describing and differentiating emotions[194]. Popular theories argue that autistic individuals' difficulties with emotion-processing are caused by co-occurring alexithymia, and are therefore not a feature of autism *per se*[207]. To date, most of the support for this hypothesis comes from studies focusing on emotion *recognition* (e.g., [209,212,213]; though see [385]). However, alexithymia is linked to proprioceptive differences (i.e., differences in perceiving the position and movement of the body[520-522]), and proprioception is essential to accurate motor control for both the body and the face (see [523-526]). Thus, it is plausible that alexithymia could be linked to differences in the *production* of facial expressions. Indeed, there is preliminary support for this idea: Trevisan and colleagues[214] identified that alexithymic, but not autistic traits, were associated with reduced expressivity of spontaneous facial expressions (here, reduced presentation duration of facial expressions) in autistic and non-autistic children. As such, any study comparing emotion recognition and production in autistic and non-autistic individuals should model the contribution of alexithymia to avoid erroneously attributing differences to autism.

In sum, it is possible that differences in the ability to recognise others' facial expressions of emotion are linked to differences in the production of those same expressions in the autistic population. However, at present research has failed to delineate clear differences in the production of emotional expression in autism because methods with low sensitivity have been used, facial morphology has not been accounted for, naturalistic movements have been underexplored and the contributions of alexithymia have not been modelled. To make progress, research that deals with these factors is needed.

When it comes to examining the relationship between production and perception an important question is *what* features of produced emotional expressions are likely to influence the perception of others' emotions? The body movement literature points a finger at relatively general aspects of movement. As noted above, individuals who generally move in a more jerky fashion show more extreme differences in labelling others' movements as natural[387]. Thus, one might predict that more jerky facial expressions are associated with reduced emotion recognition accuracy. However, a parallel literature, concerning the internal experience of emotion, draws attention to more specific features. This literature reports that the precision and differentiation of one's own emotional experiences and visual representations[425,426,469,473] may contribute to the ability to recognise the emotions of others. Indeed, this literature has its roots in signal detection theory (see [140]), where it is argued that a 'signal' distribution and a 'noise' distribution that are imprecise (i.e., wide) and indistinct (i.e., overlapping) provide a low sensitivity to discriminate between the 'signal' and 'noise'. Thus, one might predict that an individual who produces imprecise (i.e., inconsistent) angry facial expressions, which are indistinguishable from their sad expressions, may struggle to discriminate other people's angry and sad expressions (perhaps because it is difficult to determine whether others' expressions match their own for anger or for sadness). Although precision and differentiation have been explored in the emotional experience literature, these concepts are lacking from the emotional production literature.

Current Study

The current study employed facial motion capture techniques to record posed and spoken expressions of anger, happiness and sadness from autistic and, age-, gender- and IQ-matched, non-autistic adults. Facial motion capture offers many advantages with respect to the objective analysis of facial movements as it provides assessment with high temporal resolution, such that visible changes in facial movements can be tracked every few milliseconds[277]. Notably, this technique records movement of the skin surface across the whole face, and thus the resulting data directly reflect what humans see, instead of the underlying muscle contractions captured by fEMG[277]. Here we employed Apple ARKit technology, True Depth Cameras and Rokoko Face Capture tools, thus enabling us to capture up to 28,000 datapoints per recording (e.g., 52 facial landmarks across 540 timepoints). Recordings were standardised to a common avatar face to minimise effects of any morphological differences; indices were calculated representing a) the extent of activation and b) the jerkiness of movement, of numerous facial landmarks across time. We explored the contribution of both autism and alexithymia to differences in the expression of angry, happy and sad emotions. Next, we assessed whether there were any differences between the autistic and non-autistic participants in the precision and differentiation of produced facial expressions, after controlling for alexithymia. Finally, we explored whether one's own facial movement predicted the ability to recognise emotions from motion cues. More specifically, we explored whether features of participants' own emotional expressions, including jerk, activation, precision, and differentiation, contribute to participants' ability to recognise others' emotions as indexed by a dynamic emotion recognition task.

Hypotheses

Given the evidence from the body movement literature (e.g., [512-516]), we predicted that autistic participants would display significantly more jerky facial expressions than their non-autistic counterparts. We did not make any formal predictions regarding the magnitude of activation of facial landmarks since this evidence was highly mixed (e.g., [263,265-269,274,517]), and potentially confounded by alexithymia (see [146,214]). Finally, in line with signal detection theory[140] and previous findings (e.g., [426,427,469,473]), we predicted that the precision and differentiation of participants' own productions would contribute to their ability to recognise others' facial expressions.

7.2. Method

7.2.1. Participants

25 autistic and 26 non-autistic participants were recruited from local autism research databases and through a university mailing list. All autistic participants had previously received a clinical diagnosis of autism spectrum disorder from an independent clinician. The autistic participants had significantly higher autism quotient (AQ)[304] scores than the non-autistic participants (see Table 7.1). The mean AQ score in the autistic group was highly comparable to that found in large autistic population samples (e.g., 35.19 in [348]).

Table 7.1.

Means, standard deviations, and group differences of participant characteristics. In the central columns, means are followed by standard deviation in parentheses.

Variable	Non-autistic (n = 26)		Autistic (n = 25)		Significance
Gender	16	Cisgender female	12	Cisgender female	.777
	8	Cisgender male	10	Cisgender male	
	1	Non-binary/ Third gender	1	Non-binary/ Third gender	
	1	Prefer not to say	1	Prefer not to say	
	0	Transgender male	1	Transgender male	
Age	27.73 (10.69)		29.92 (9.67)		.448
IQ	116.85 (13.06)		112.60 (19.88)		.375
AQ	13.81 (7.62)		33.24 (9.13)		< .001
TAS-20	43.12 (13.58)		62.24 (12.11)		< .001

Note. Age is in years.

7.2.2. Procedures

First, participants completed demographics questions, the autism quotient (AQ)[304] and the Toronto Alexithymia Scale (TAS-20)[344] on Qualtrics (see Chapter 2 for a full description of these questionnaires), and then the PLF Emotion Recognition Task[239,385] (as in Chapter 2) on Gorilla.sc (access task at: https://app.gorilla.sc/openmaterials/447800). These tasks were completed online prior to the testing session. On the day of the testing session, participants completed our FaceMap paradigm and then the two-subtest version of the Weschler Abbreviated Scale for Intelligence (2nd edition; WASI-II)[527].

7.2.3. Materials and stimuli

FaceMap

To examine the facial expressions produced by the autistic and non-autistic participants, we used our FaceMap paradigm. In this task, participants' facial movements were recorded during two conditions (as in [239]). In the spoken condition, participants were required to say a sentence ("My name is Jo and I'm a scientist) whilst moving their face in a way which displayed the target emotion. In this condition, participants completed 2 practice trials and then two experimental blocks: in each block participants posed eight angry, eight happy, and eight sad expressions (the order of these emotional displays was counterbalanced across participants). In the posed condition, participants were required to pose the target emotional expressions along to a series of beeps (which varied in pitch). On the first beep participants posed a neutral expression; on the second beep participants moved into target emotional expression; on the third beep participants moved back into a neutral expression, and then finally a fourth beep indicated that the recording had finished (3 second delay between each beep; 9 second duration). In the posed condition, participants completed 2 practice trials followed by two experimental blocks: in each block participants posed eight angry, eight happy, and eight sad expressions (the order of these was counterbalanced across participants). In total, there were 96 recordings per participant (48 spoken, 48 posed), thus generating over 4,800 facial expression recordings.

To facilitate these recordings, participants stood 30cm away from, and facing, an iPhone 12 that was mounted on a tripod with an illuminated ring light. The facial expressions were recorded and tracked using the *Rokoko Face Capture* tool. Rokoko employs *Apple ARKit* technology, which has been validated for facial motion tracking[528], and is recommended for analysing the facial movements of those with movement-related disorders (e.g., autism)[528]. The *ARKit* technology makes use of mobile iOS devices equipped with a True Depth Camera, which can record high resolution (1920 x 1080 pixels) videos at a variety of frame rates (here, 60 frames per second). This True Depth Camera has an infrared emitter capable of projecting over 30,000 invisible dots to create an infrared image representation of the face[529,530], which can be then used to extract the X, Y, and Z coordinates of specific points, and levels of activation of 52 facial blendshapes (i.e., action units; see below). Before its release, this technology was extensively tested with individuals of different ages and ethnic backgrounds[531], thus making it a suitable for tracking the facial movements of those with varied face morphology.

WASI-II

The Intelligence Quotient (IQ) of participants was assessed via the two-subtest version of the WASI-II[527]. The two-subtest form consists of vocabulary and matrix reasoning assessments. Scores on the WASI range from 70 to 160, with higher scores representing higher intelligence, and with 100 corresponding to average intelligence. The two-subtest version of the WASI-II demonstrates good psychometric properties, including high split-half, ($r \geq 0.8$) and test-retest, reliability ($r \geq 0.8$)[532].

7.2.4. Data processing and extraction

As previously discussed, preliminary literature suggests possible differences in facial morphology between autistic and non-autistic individuals (e.g., [279-282]). In the current study, we aimed to compare the facial *movements* of autistic and non-autistic individuals when posing different emotional expressions, and thus it was necessary to control for differences in facial morphology across participants. To do so, the facial expression recordings were retargeted onto photorealistic avatars (using *Blender)* before the data were extracted (see https://osf.io/8a5yw/).

We extracted the data in two forms. Firstly, we extracted the X, Y, and Z coordinates of the 68 facial landmarks analysed by the popular open-source software OpenFace. Next, we calculated jerk at each of the facial landmarks at each of the timepoints in the recordings by first calculating the distance that each facial landmark had moved as the square root of the sum of squared differentials of the x, y, and z co-ordinates for each point, and subsequently calculating movement speed by dividing the distance travelled by time. Acceleration was indexed as the change in speed at each of the facial landmarks across two adjacent timepoints. Jerk was calculated as the change in acceleration at each of the facial landmarks across two adjacent timepoints. Consequently, we had jerk data for all landmarks on the face (68) across all timepoints in the video (378 in spoken condition, 536 in posed condition) for angry, happy, and sad expressions (96), of all participants (51).

Next, we extracted the activation of 52 facial action "*blendshapes*" across all timepoints (see https://arkit-face-blendshapes.com for full list of blendshapes). To extract this information, the infrared face map (described above) is analysed using Apple's built-in neural network algorithm[533]. The extracted blendshapes are similar to facial action units (e.g., "browInnerUp", "mouthSmileLeft", etc.). Activation scores for each blendshape range from zero, no activation, to one, peak activation. Since we aimed to examine facial movements specifically, we excluded eight blendshapes that corresponded to where participants were looking (e.g., the left and right Eye Look Up, Eye Look Down, Eye Look In and Eye Look Out blendshapes). As such, here we analysed activation data for 44 blendshapes across all timepoints in the video (382 in spoken condition, 540 in posed condition) for the angry, happy, and sad expressions (96), of all participants (51). These data are particularly useful for assessing spatial differences in facial expressions between the groups. Notably, the point at which participants are at peak activation in the posed condition is timepoint 270 of 540.

Resampling Spoken Recordings

After extracting the jerk and activation data for the spoken expressions, we resampled these data (using the resample() function in MATLAB) such that all recordings were equal in length, thus facilitating statistical comparisons. Since all recordings in the posed condition were equal in length, no resampling was necessary for these expressions.

Score calculations

As discussed previously, we theorised that the intensity, precision (i.e., consistency of same emotional expression) and differentiation (i.e., differentiation across different emotional expressions) of one's own facial expressions could contribute to the ability to recognise others' expressions. As such, we calculated measures of intensity, precision and differentiation for the posed and spoken expressions in terms of both jerk and activation.

"Intensity", for each participant, was indexed by calculating the mean of a) jerk and b) activation across timepoints, landmarks and repetitions, for each emotion and condition, and subsequently averaging across emotions to get an index of overall mean jerk and activation for posed and spoken expressions.

Precision scores were calculated in four steps: for each participant and for each emotion (1) we calculated a mean of jerk, and activation, across all timepoints in the recording for each landmark/blendshape and repetition; (2) we computed the standard deviation of these averaged jerk and activation scores across the 16 repetitions for each landmark/blendshape, thus giving us an index of variability in jerk and activation at each of the landmarks/blendshapes; (3) we calculated a mean of these variability scores across the landmarks to give us one overall measure of variability; (4) we multiplied the variability scores by -1 such that the mean variability scores would represent mean precision. By following these steps, we calculated precision for angry, happy, and sad posed and spoken expressions in terms of both jerk and activation. We took a mean across emotions to get an index of overall mean precision for posed and spoken expressions with respect to jerk and activation.

To calculate distance scores, we followed three steps: for each participant (1) we calculated a mean of jerk, and activation, across the 16 repetitions, and across all timepoints, for each landmark/blendshape; (2) we computed the absolute difference in jerk, and in activation, for the angry and happy, angry and sad, and happy and sad facial expression pairs at each of the landmarks/blendshapes; (3) we took an average of these difference scores across landmarks/blendshapes to reach one difference score for each facial-expression-pair (one difference score for angry and happy expressions; one difference score for angry and sad expressions, and one difference score for happy and sad expressions). Following this, we took a mean across facial-expression-pairs to get an index of overall mean distance for posed and spoken expressions with respect to jerk and activation.

7.2.5. Data Analysis

Our analyses comparing the facial expressions produced by autistic and non-autistic individuals were conducted using MATLAB (version 2022b). The analyses assessing the contribution of emotion-production factors to emotion recognition were conducted using R Studio (version 2021.09.2) and JASP (version 0.17.2.1). For all permutation test analyses comparing autistic and non-autistic facial expressions (see description below), we employed an alpha of 0.05 to determine statistical significance. For all Bayesian analyses, we followed the classification scheme used in JASP: BF_{10} values between one and three reflect weak evidence, between 3 and 10 reflect moderate evidence, greater than 10 reflect strong evidence, and greater than 100 reflect extreme evidence for the experimental hypothesis[352]. For all our Bayesian linear regressions, we used a default Zellner-Siow Prior (r scale = 0.354).

7.3. Results

To portray the contribution of autism and alexithymia to the production of angry, happy and sad facial expressions across time, we rendered heatmaps of the average expressions produced by the autistic and non-autistic participants, and those high and low in alexithymia (see Appendix 6.1).

7.3.1. Analyses with posed data

Activation at the peak of posed expressions

First, we aimed to determine whether there were group differences in activation during peak expression for anger, happiness and sadness at specific blendshapes. Therefore, we extracted the activation data at peak expression (i.e., at timepoint 270) for each blendshape, participant, and repetition, for each of the emotions respectively (44 blendshapes x 51 participants x 16 repetitions; resulting in 35,904 datapoints for each emotion). Following this, for each of the 44 blendshapes, we conducted a linear mixed effects model of activation as a function of group and TAS score, with subject and repetitions as random intercepts (816 datapoints for each model), for each of the emotions. In these models, if we found a significant main effect of group, this would suggest that there are significant differences in activation between autistic and non-autistic individuals at the specific blendshape, even after controlling for alexithymia.

To account for multiple comparisons, we carried out a permutation test (with 100 permutations). Within each permutation, the activation data for participants were shuffled so that they were randomly allocated to either the autistic or non-autistic group (and as such the data were shuffled amongst individuals with differing alexithymia scores). Following this, we conducted linear mixed models predicting (shuffled) activation at each blendshape with group, TAS score, and with subject and repetition as random intercepts (as above). The F values for the group and alexithymia effects on activation were extracted in each permutation. Next, all the F values for the shuffled data were sorted in order of magnitude. Finally, the effects in our analysis with true participant data were deemed to be significant if they exceeded the F value at the 95th percentile (and thus alpha < .05) from the analysis with the shuffled data.

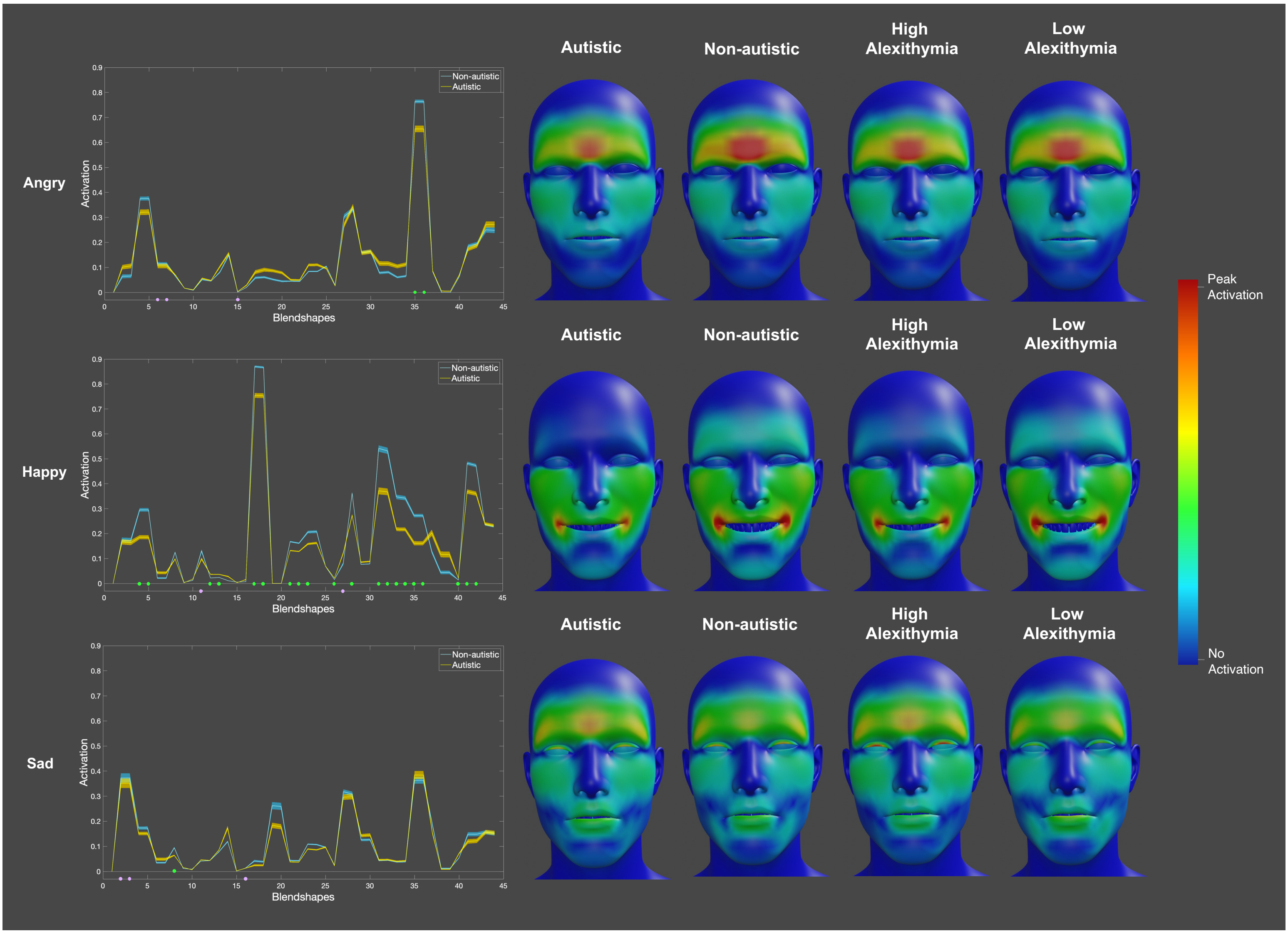
This analysis identified that there were significant group differences in activation at specific blendshapes for the angry [4.55% of blendshapes], happy [45.55% of blendshapes] and sad [2.27% of blendshapes] expressions, even after controlling for alexithymia. When posing an angry expression, the autistic participants exhibited significantly lower activation of the left and right brow down blendshapes [left F = -4.91; right F = -4.91] – facial features typically considered to signal anger. Alexithymia was a significant negative predictor of activation for the left and right eye wide [left F = -5.47; right F = -5.49] and the left mouth [F = -5.47] blendshapes. For happiness, the autistic participants displayed significantly lower activation at 45.55% of the blendshapes; the left and right eye squint [left F = -8.40; right F = -8.43], mouth smile [left F = -15.67; right F = -14.97], mouth dimple [left F = -7.84; right F = -6.82], mouth lower down [left F = -5.80; right F = -5.63], mouth upper up [left F = -8.55; right F = -8.31], brow down [left F = -7.13; right F = -7.12], and cheek squint [left F = -10.43; right F = -11.05] blendshapes, along with the upper mouth roll [F= -4.54], upper mouth shrug [F = -5.43], mouth close [F = -5.39], mouth funnel [F = -5.18], left mouth stretch [F = -3.72] and cheek puff [F = -4.34] blendshapes (see Figure 7.1). Thus, the autistic participants displayed lower activation of many blendshapes considered to signal happiness (e.g., mouth smile, cheek squint). Alexithymia was a significant positive predictor of activation for the jaw open [F = 5.07] and a negative predictor of the mouth shrug lower [F = -5.94] blendshapes. Finally, for sadness, the autistic participants exhibited significantly lower activation for the jaw forward [F = 4.02] blendshape. Alexithymia was a significant positive predictor of activation for the left and right eye blink [left F = 5.86; right F = 5.94], and the right mouth [F = 4.02] blendshapes (see Figure 7.1).

Activation at the peak of posed expressions: Summary

At the peak of the posed expressions, an autism diagnosis was associated with reduced activation of a number of emotion-relevant blendshapes. These likely indicate reduced eyebrow movements for anger, less eye, eyebrow, mouth and cheek activity for happiness and reduced jaw movement for sadness. Alexithymia was linked to different expressions which featured both reduced and increased activation. That is, individuals high in alexithymia showed reduced mouth movements for both anger and happiness, but for sadness these individuals exhibited increased activity around the mouth region.

Figure 7.1.

Graphs (left) and heatmaps (right) showing the activation of posed angry (top), happy (middle) and sad (bottom) autistic (orange) non-autistic (blue) facial expressions across blendshapes.



Note. In the left panel, significant group effects are indicated by green dots on the graph, and significant alexithymia effects are indicated by lilac dots. Note that the heatmaps for the expressions are standardised for each emotion respectively.

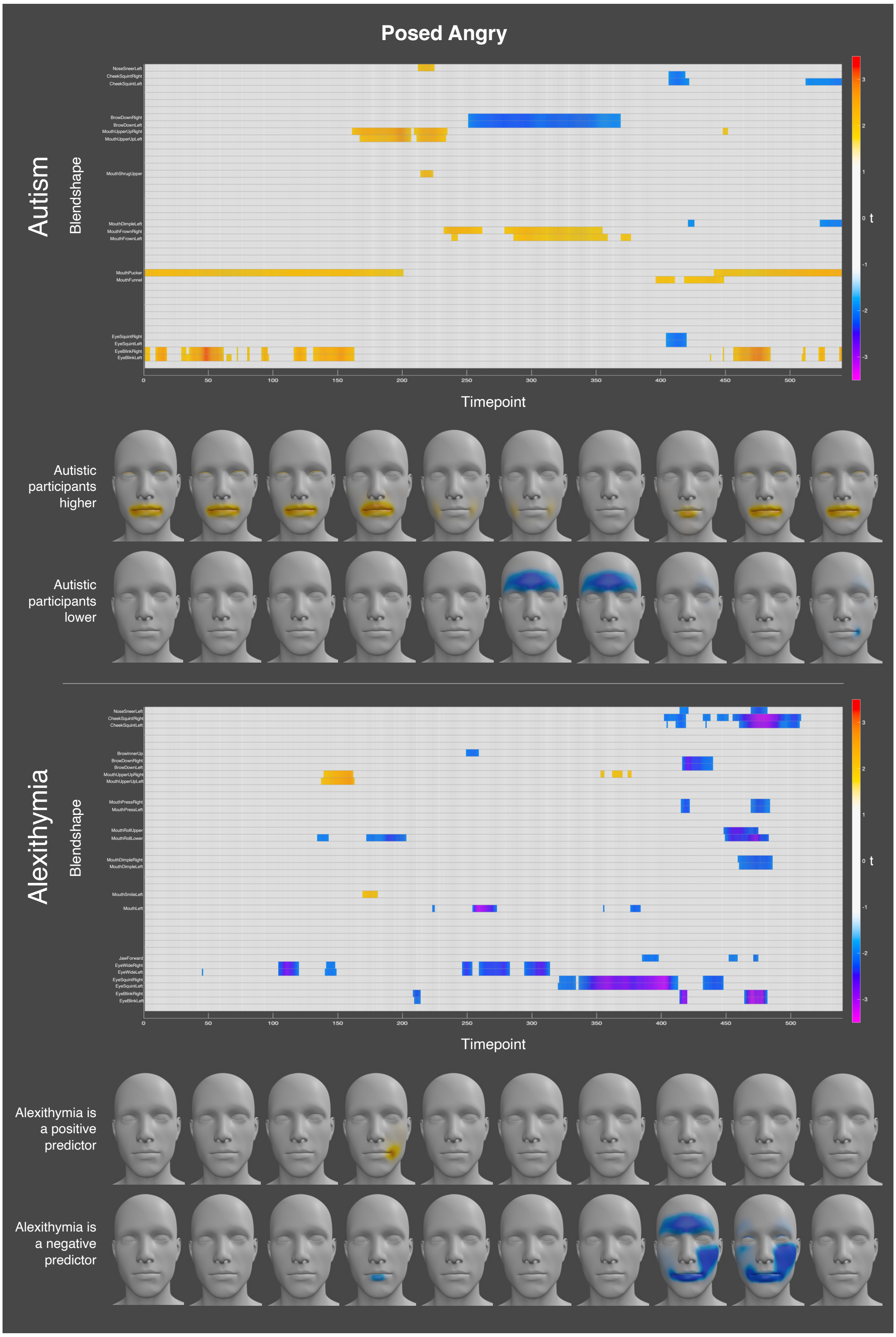
Activation across the time-course of posed expressions

Next, we aimed to determine whether there were any differences between groups in activation for angry, happy and sad facial expressions at specific blendshapes and timepoints in the posed condition. To test this, for each of the 44 blendshapes, at each of the timepoints, we conducted a linear mixed effects model of activation as a function of group and TAS score, with subject and repetitions as random intercepts, for each of the emotions. In these models, if we found a significant main effect of group, this would suggest that there are significant differences in activation between autistic and non-autistic individuals at the specific blendshape, at the specific moment in time, after controlling for alexithymia. As above, we conducted a permutation test to determine which effects were statistically significant.

This analysis identified that there were significant group differences in activation for angry, happy, and sad facial expressions at specific blendshapes at specific timepoints. For anger, the autistic participants displayed significantly lower activation of the left and right brow down blendshapes for numerous timepoints when holding the angry expression (see Figure 7.2). In contrast, the autistic participants displayed significantly higher activation of the left and right mouth frown and mouth upper blendshapes during this period. Thus, when producing posed expressions of anger, the autistic participants may have relied more on the mouth, and less on the eyebrows, to signal anger. Prior to and after the expression, the autistic participants also displayed higher activation for the mouth pucker and left and right eye blink blendshapes. Alexithymia was a significant negative predictor of activation for the left and right eye wide and eye squint blendshapes when holding the angry expression (see Figure 7.2 for all significant effects).

Figure 7.2.

Graphs showing the t-values for the significant group (top) and alexithymia (bottom) effects on activation across blendshapes and time for angry posed expressions.

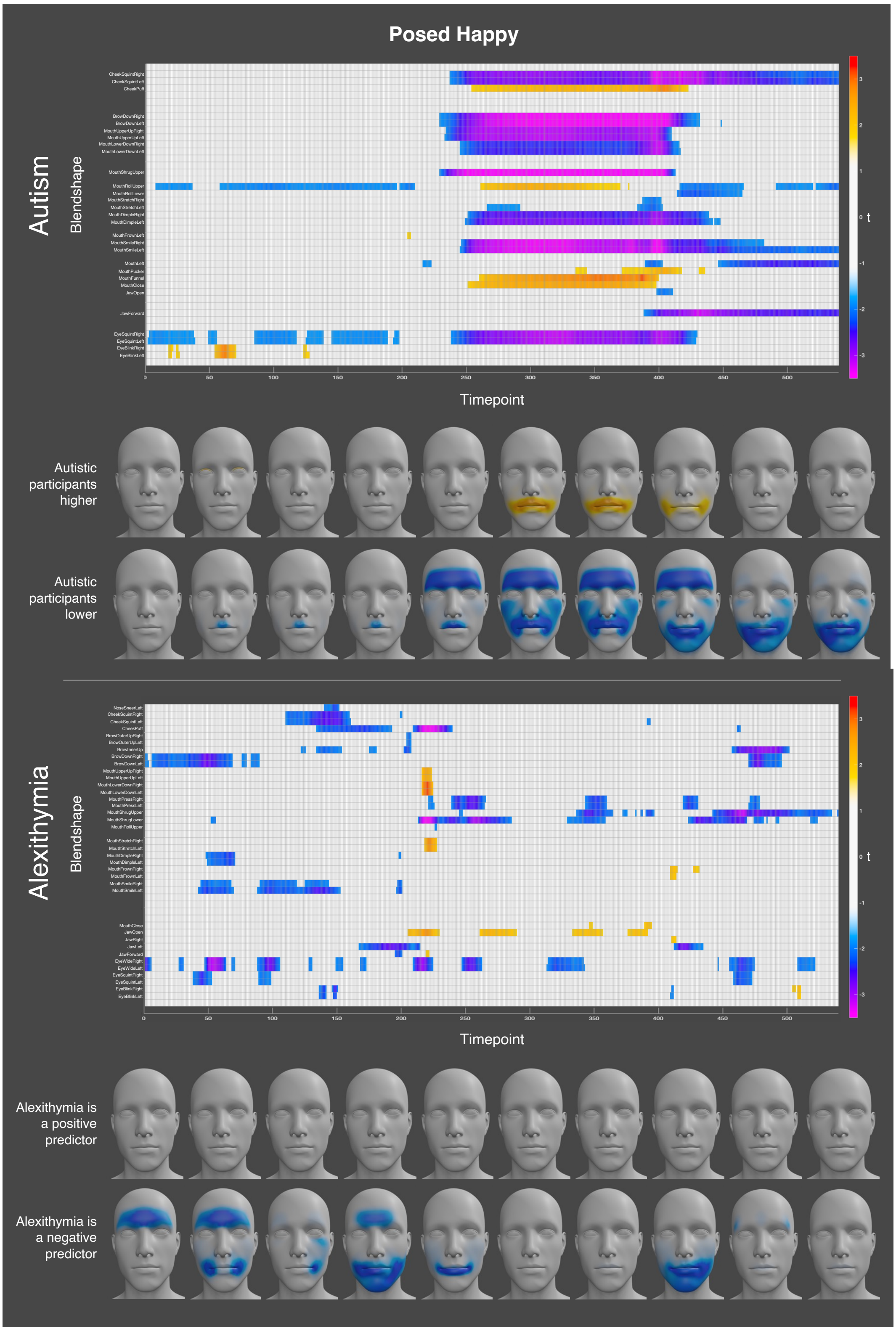


Note. Positive values (e.g., orange, red) signify higher activation in the autistic participants or a positive predictive relationship between activation and alexithymia. Negative values (e.g., blue and purple) signify lower activation in the autistic participants or a negative predictive relationship between activation and alexithymia. This graph also features heatmaps to help readers visualise the significant effects. The heatmaps show the significant differences at every second from the start to end of the recording (0, 1, 2, 3, 4, 5, 6, 7, 8, and 9 seconds).

For happiness, the autistic participants displayed significantly lower activation of the left and right mouth smile, mouth dimple, mouth shrug upper, mouth lower down, mouth upper up, eyebrow down and eye squint blendshapes at specific timepoints when holding the expression. In contrast, the autistic participants displayed significantly higher activation at the mouth close, mouth funnel, mouth roll upper, and cheek puff blendshapes during this period (see Figure 7.3). These results suggest that the autistic and non-autistic participants display different mouth and cheek configurations when expressing happiness. Alexithymia was a significant negative predictor of activation for the left and right eye wide, mouth press, and the upper and lower mouth shrug blendshapes at peak expression. Conversely, alexithymia was a significant positive predictor of activation for the left and right mouth lower down and mouth upper up blendshapes, at timepoints immediately following the initiation of movement into the happy expression. Alexithymia was also a significant predictor of the jaw open blendshape at numerous timepoints when holding the expression (see Figure 7.3).

Figure 7.3.

Graphs showing the t-values for the significant group (top) and alexithymia (bottom) effects on activation across blendshapes and time for happy posed expressions.



Note. Positive values (e.g., orange, red) signify higher activation in the autistic participants or a positive predictive relationship between activation and alexithymia. Negative values (e.g., blue and purple) signify lower activation in the autistic participants or a negative predictive relationship between activation and alexithymia. This graph also features heatmaps to help readers visualise the significant effects. The heatmaps show the significant differences at every second from the start to end of the recording (0, 1, 2, 3, 4, 5, 6, 7, 8, and 9 seconds).

Finally, for sadness, the autistic participants displayed significantly lower activation of the left jaw blendshape at numerous timepoints when holding the expression. In contrast, the autistic participants exhibited significantly higher activation of the left and right mouth upper up blendshapes at timepoints shortly after initiating movement into the expression (see Figure 7.4). Alexithymia, on the other hand, was a significant negative predictor of the left and right mouth lower down, mouth upper up, mouth stretch, the upper mouth roll and right jaw blendshapes during this period. Conversely, alexithymia was a significant positive predictor of activation for the left and right eye blink and the mouth right blendshapes at specific timepoints when holding the expression (see Figure 7.4).

Figure 7.4.

Graphs showing the t-values for the significant group (top) and alexithymia (bottom) effects on activation across blendshapes and time for sad posed expressions.

Note. Positive values (e.g., orange, red) signify higher activation in the autistic participants or a positive predictive relationship between activation and alexithymia. Negative values (e.g., blue and purple) signify lower activation in the autistic participants or a negative predictive relationship between activation and alexithymia. This graph also features heatmaps to help readers visualise the significant effects. The heatmaps show the significant differences at every second from the start to end of the recording (0, 1, 2, 3, 4, 5, 6, 7, 8, and 9 seconds).

Activation across the time course of posed expressions: Summary

For posed expressions, there were differences in the time-course of activity between autistic and non-autistic individuals. For anger this included enhanced activity around the mouth and reduced activity around the eyebrows, suggesting a greater reliance on mouth cues for autistic individuals. For happiness, the autistic participants displayed greater activity at some mouth blendshapes, and lower activity at others, suggesting a mouth configuration that differed from their non-autistic peers. Concurrently there was lower activity around the eyes, eyebrows and cheeks for autistic individuals, suggesting a smile that does not "reach the eyes". For sadness, the autistic participants displayed greater activation of the upper lip, and lower protrusion of the jaw.

Alexithymic traits were also associated with differences in the time-course of posed emotional expressions. For anger, high levels of alexithymic traits were linked to lower activation around the eye region. For happiness, alexithymia was linked to reduced activity around the eyes, eyebrows, and mouth, which is suggestive of reduced smile activity. For sadness, alexithymia was associated with reduced activity around the mouth.

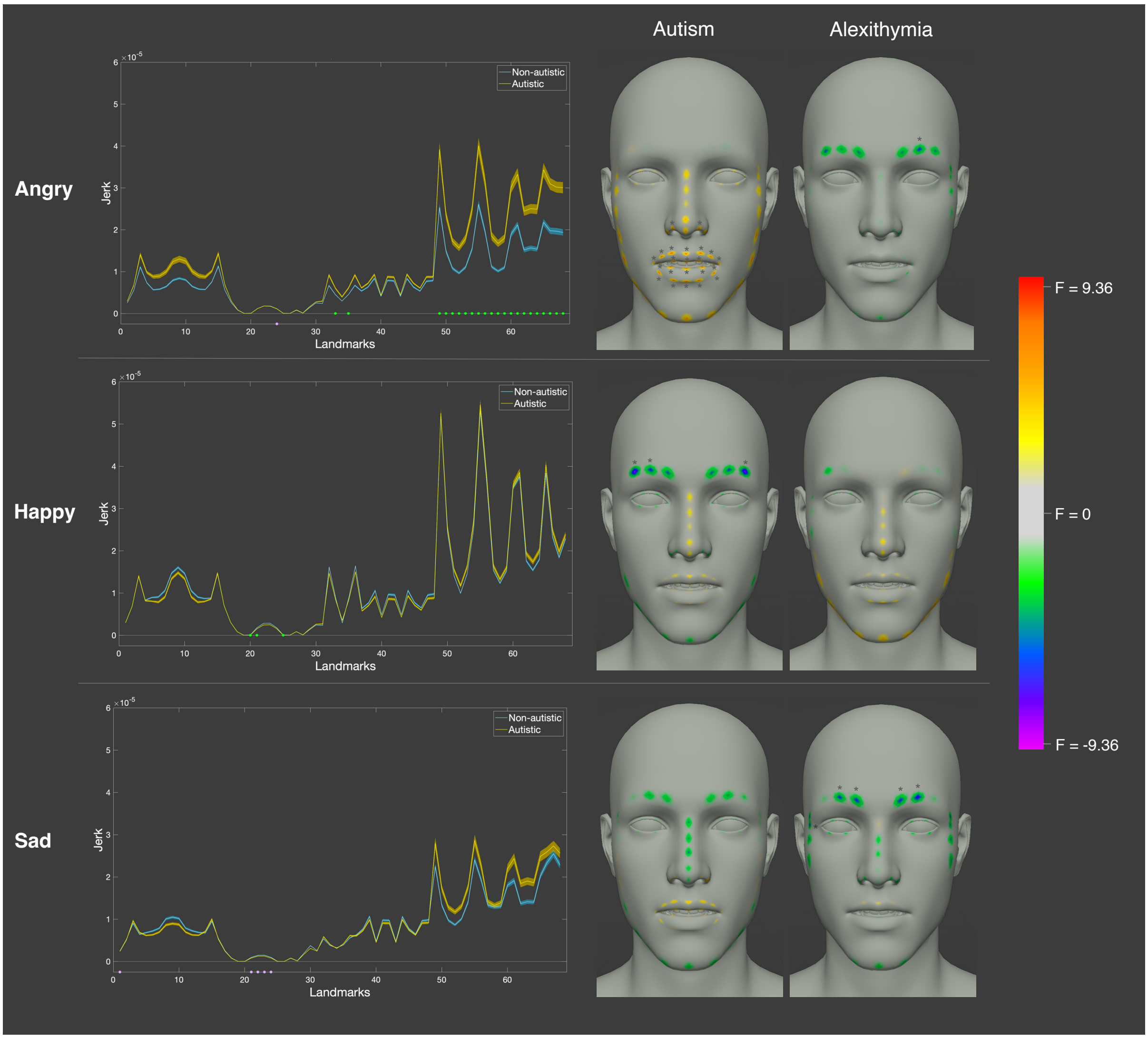
Jerk averaged across the whole time-course of posed expressions

Next, we aimed to determine whether there were differences between groups in the jerkiness of angry, happy and sad expressions at specific landmarks on the face. Due to previous findings that autistic individuals exhibit significantly more jerky movements, independent of movement phase (see [387]), we took an average of jerk across all timepoints in the recording for each landmark, participant, and repetition, for each of the emotions respectively (68 landmarks x 51 participants x 16 repetitions; resulting in 55,488 datapoints for each emotion). Following this, for each of the 68 landmarks, we conducted a linear mixed effects model of jerk as a function of group and TAS scores, with subject and repetition as random intercepts (816 datapoints for each model) for each of the emotions. As previously, we conducted a permutation test on the data to account for multiple testing (see above).

This analysis revealed that there were significant group differences in jerk for angry and happy (but not sad) expressions at specific regions on the face (note that the largest number of significant differences were found for anger = 32.35% landmarks; happiness = 4.41% landmarks). When posing angry expressions, the autistic participants exhibited significantly higher jerk than the non-autistic participants at all of the mouth facial landmarks [mean significant F = -4.19] and at specific nose landmarks [22.2% landmarks; mean significant F = -3.71], even after controlling for alexithymia (see Figure 7.5). Combining these results with those relating to activation, our findings suggest that the autistic participants may activate the mouth region to a greater extent when expressing anger, thus leading to greater jerk in this region. In addition, this analysis revealed that alexithymia was a significant negative predictor at specific eyebrow landmarks [10% landmarks; mean significant F = -3.87]: those higher in alexithymia exhibited lower jerk at a specific eyebrow landmark when posing anger (see Figure 7.5). In contrast, for happiness, the autistic participants displayed significantly *lower* jerk at a third of the eyebrow landmarks (33.33% landmarks; mean significant F = 7.62). It is likely that the autistic participants displayed significantly lower jerk at the eyebrow region due to there being lower activation of the left and right 'eyebrow down' blendshapes, as per our previous analysis. Alexithymia was not a significant predictor of jerk at any of the landmarks when posing happiness. Finally, there were no significant group differences in jerk for sad expressions at any of the facial landmarks. Nevertheless, alexithymia was a significant negative predictor of jerk at specific eyebrow [40% landmarks; mean significant F = - 4.56] and jaw [F = 5.88%; F = 3.76] landmarks: those higher in alexithymia exhibited less jerky movements at specific eyebrow landmarks when posing sadness (see Figure 7.5).

Figure 7.5.

Graphs showing the jerkiness of posed angry (top), happy (middle) and sad (bottom) autistic (orange) and non-autistic (blue) facial movements across facial landmarks.



Note. In the left panel, facial landmarks where there are significant group differences are shown in green, and facial landmarks where alexithymia contributes to jerk are shown in lilac. In the right panel, the F values for the group and alexithymia effects at each facial landmark are shown. Positive values (e.g., yellow, orange, red) signify higher jerk in the autistic participants or a positive predictive relationship between jerk and alexithymia. Negative values (e.g., green, blue and purple) signify lower jerk in the autistic participants or a negative predictive relationship between jerk and alexithymia. Stars denote statistical significance at $p < .05$.

Jerk averaged across the whole time-course of posed expressions: Summary

For posed expressions, there were differences in the jerkiness of facial movements between autistic and non-autistic individuals. In line with our above observation that autistic participants activate the mouth region to a greater extent than non-autistic participants, we further observed more jerky mouth movements for angry expressions. For happiness, the autistic participants displayed less jerky eyebrow movements which, again, is in line with lower activation in this region. Alexithymia was also associated with some differences in the jerkiness of expressions. Specifically, those higher in alexithymia exhibited less jerky eyebrow movements when posing anger and sadness.

7.3.2. Analyses with spoken data

Activation averaged across the whole time-course of spoken expressions

Next, we aimed to determine whether there were group differences in activation for the angry, happy, and sad *spoken* expressions at specific blendshapes. In this condition, since the expression was produced across the whole recording, we took an average of activation across all timepoints for each blendshape, participant, and repetition, for each of the emotions respectively (52 blendshapes x 51 participants x 16 repetitions; resulting in 42,432 datapoints for each emotion). Following this, for each of the 44 blendshapes, we conducted a linear mixed effects model of activation as a function of group and TAS score, with subject and repetitions as random intercepts (816 datapoints for each model), for each of the emotions. To account for multiple testing, we conducted a permutation test (see above).

This revealed that there were significant group differences in activation for spoken expressions of anger [15.91% of blendshapes], happiness [11.36% of blendshapes] and sadness [4.55% blendshapes]. For anger, the autistic participants displayed significantly lower activation of the left and right eye squint [left $F = -4.93$; right $F = -4.91$], brow down [left $F = -3.70$; right $F = -3.70$], and the mouth roll upper [$F = -5.90$] blendshapes, and significantly higher activation of the left and right mouth upper up [left $F = 3.94$; right $F = 4.70$] blendshapes. Thus, across both the posed and spoken condition, the autistic participants displayed lower activation of the brow down blendshapes. Notably, alexithymia was a significant positive predictor of activation at the left and right mouth smile [left $F = 8.30$; right $F = 8.97$], cheek squint [left $F = 4.21$; right $F = 3.82$] and left mouth [$F = 6.88$] blendshapes (see Figure 7.6). Hence, those high in alexithymic traits showed increased activation of many of the blendshapes associated with happiness (mouth smile, cheek squint) when posing anger, suggesting that these facial expressions may be less well differentiated. For happy spoken expressions, the autistic participants exhibited significantly lower activation of the left and right eye squint [left $F = -4.12$; right $F = -4.12$], and brow down [left $F = -10.45$; right $F = -10.42$], and the mouth roll lower [$F = -3.78$] blendshapes (see Figure 7.6). Thus, across both conditions, the autistic participants displayed lower activation of the brow down blendshapes when expressing happiness. In addition, alexithymia was a significant positive predictor of the left and right mouth frown blendshapes [left $F = 5.35$; right $F = 5.91$], and a significant negative predictor of activation for right jaw blendshape [$F = - 4.39$]. Hence, when posing happiness, those high in alexithymic traits showed increased activation of some of the blendshapes associated with anger (e.g., mouth frown), suggesting once again that their happy expressions may be less well-differentiated from their angry expressions. Finally, for sad spoken expressions, the autistic participants displayed higher activation of the left and right mouth upper up [left F = 8.39; right F = 9.63] blendshapes (see Figure 7.6). Alexithymia was not a significant predictor of activation for sad spoken expressions at any of the blendshapes.

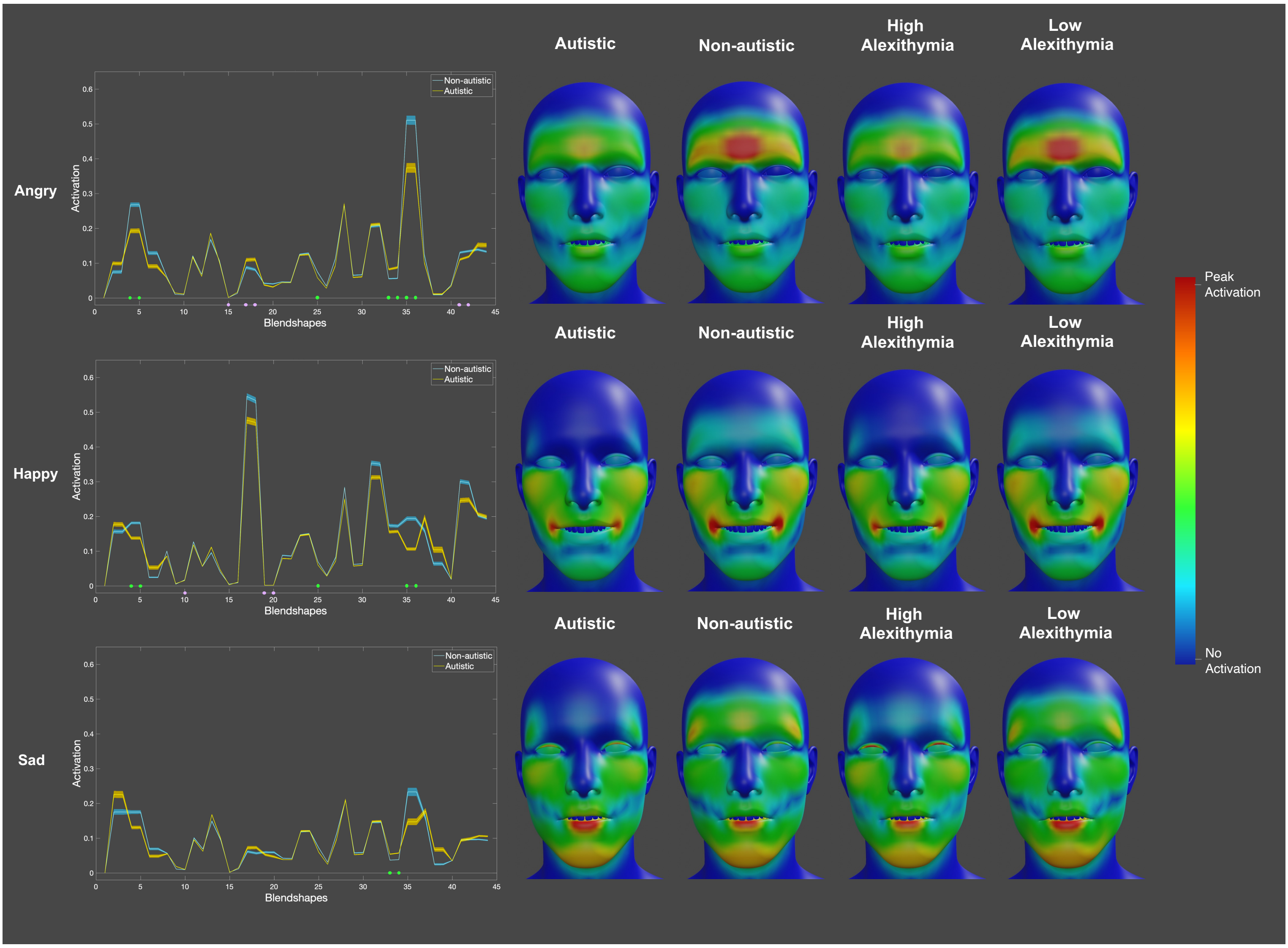
Activation averaged across the whole time-course of spoken expressions: Summary

When activation was averaged across the whole time-course of spoken expressions we observed that, compared to non-autistic individuals, those with an autism diagnosis exhibit reduced activity in the eye and eyebrow regions when speaking in an angry fashion. Similarly, the autistic participants showed reduced activity around the eye and eyebrows when speaking in a happy fashion, suggesting that a smile that does not 'reach the eyes' (as much as for their non-autistic peers). When speaking in a sad fashion, the autistic participants show increased activity around the upper lip, mirroring the observations we made for posed expressions.

Alexithymia was associated with activation of many of the blendshapes associated with happiness (mouth smile, cheek squint) when posing anger, and activation of anger-associated blendshapes when posing happiness. Thus, suggesting that these facial expressions may be less well differentiated for highly alexithymic individuals.

Figure 7.6.

Graphs (left) and heatmaps (right) showing the activation of spoken angry (top), happy (middle) and sad (bottom) autistic (green) non-autistic (purple) facial expressions across blendshapes.



Note. In the left panel, significant group effects are indicated by green dots on the graph, and significant alexithymia effects are indicated by lilac dots. Note that the heatmaps for the expressions are standardised for each emotion respectively.

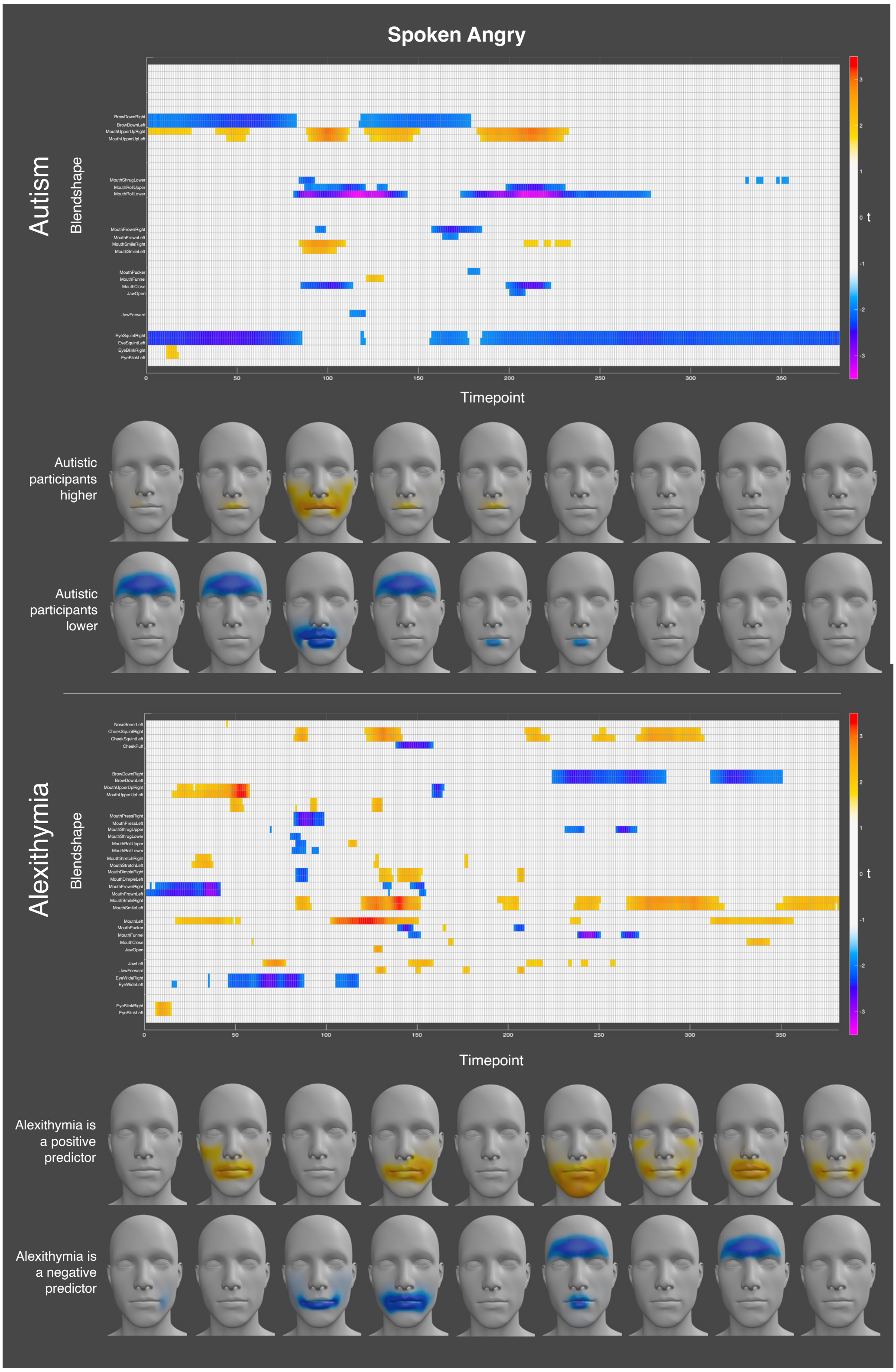
Activation across the time-course of spoken expressions

Next, we aimed to determine whether there were any differences between groups in activation for angry, happy and sad facial expressions at specific blendshapes, at specific timepoints in the spoken expression. To test this, for each of the 44 blendshapes, at each of the timepoints, we conducted a linear mixed effects model of activation as a function of group and TAS score, with subject and repetitions as random intercepts, for each of the emotions. As above, we employed a permutation test to establish which effects were statistically significant.

This analysis revealed that, for anger, the autistic participants displayed significantly lower activation of the left and right brow down and eye squint, the lower and upper mouth roll, and the mouth close blendshapes at numerous timepoints throughout the expression. In contrast, the autistic participants displayed significantly higher activation of the left and right mouth upper up blendshapes at numerous timepoints throughout, and the mouth smile blendshapes early in the angry expression (see Figure 7.7 for all significant differences). Alexithymia was a significant positive predictor of the left and right mouth smile and cheek squint blendshapes at numerous timepoints throughout the angry expression, thus suggesting that angry and happy expressions are less well differentiated for highly alexithymic individuals. In comparison, alexithymia was a significant negative predictor of the brow down blendshapes later in the expression (see Figure 7.7 for all significant differences).

Figure 7.7.

Graphs showing the t-values for the significant group (top) and alexithymia (bottom) effects on activation across blendshapes and time for angry spoken expressions.

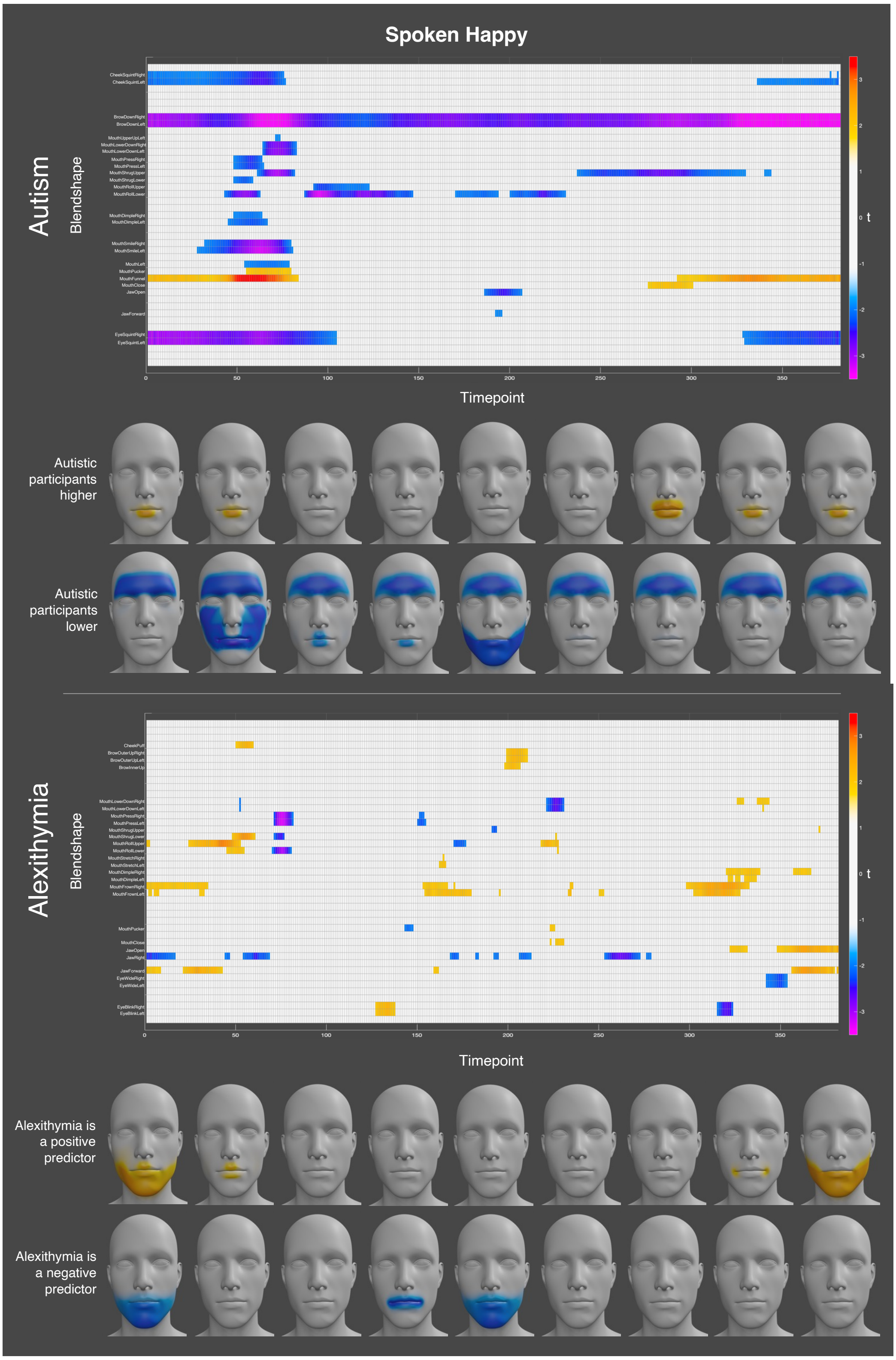


Note. Positive values (e.g., orange, red) signify higher activation in the autistic participants or a positive predictive relationship between activation and alexithymia. Negative values (e.g., blue and purple) signify lower activation in the autistic participants or a negative predictive relationship between activation and alexithymia. This graph also features heatmaps to help readers visualise the significant effects. The heatmaps show the significant differences at 0.8 second intervals (48 frames).

For happiness, the autistic participants exhibited significantly lower activation of the left and right brow down blendshapes at every timepoint in the recording. In addition, the autistic participants displayed significantly lower activation of the left and right cheek squint, eye squint and mouth shrug upper blendshapes at the start and end of the expression, and many of the mouth-related blendshapes (e.g., left and right mouth lower down, mouth smile, mouth dimple, mouth press, etc) at the start of the expression. In contrast, the autistic participants displayed significantly higher activation of the mouth pucker and mouth funnel blendshapes at the start and end of the expression. Alexithymia, on the other hand was a significant positive predictor of the left and right mouth frown blendshapes at numerous timepoints throughout, suggesting that highly alexithymic individuals tend to activate action units associated with anger when posing happiness (see Figure 7.8 for all significant effects).

Figure 7.8.

Graphs showing the t-values for the significant group (top) and alexithymia (bottom) effects on activation across blendshapes and time for happy spoken expressions.

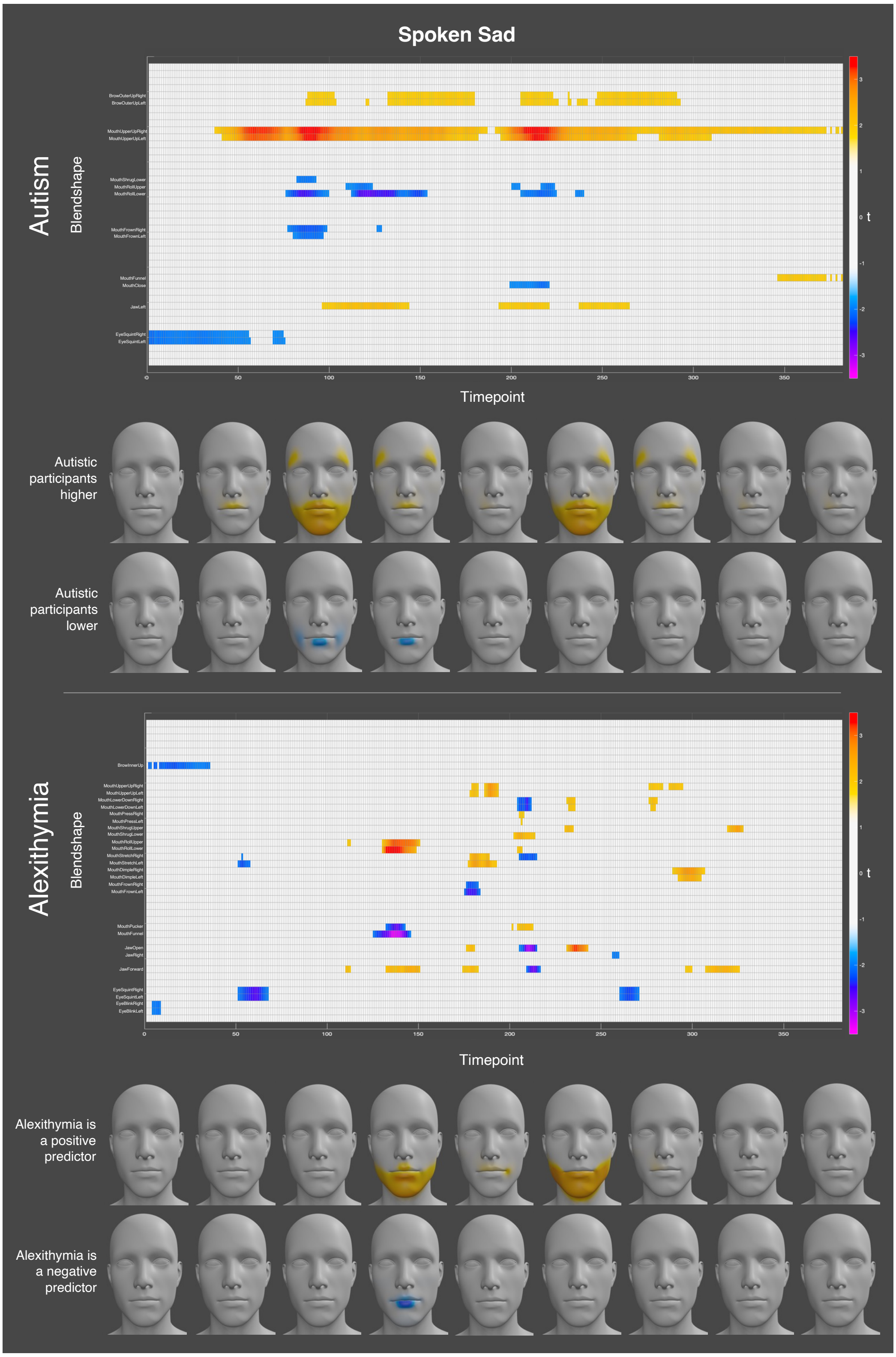


Note. Positive values (e.g., orange, red) signify higher activation in the autistic participants or a positive predictive relationship between activation and alexithymia. Negative values (e.g., blue and purple) signify lower activation in the autistic participants or a negative predictive relationship between activation and alexithymia. This graph also features heatmaps to help readers visualise the significant effects. The heatmaps show the significant differences at 0.8 second intervals (48 frames).

Finally, for sadness, the autistic participants displayed significantly higher activation of the left and right mouth upper up and brow outer up blendshapes, along with the left jaw blendshape, at numerous timepoints throughout the expression. Concurrently, the autistic participants exhibited significantly lower activation of the upper and lower mouth roll, and lower mouth shrug blendshapes throughout the expression. Finally, the autistic participants displayed lower activation of the left and right eye squint and mouth frown blendshapes near the start of the expression (see Figure 7.9). Alexithymia was a significant positive predictor of the upper and lower mouth roll and mouth shrug blendshapes, and the left and right mouth upper up and mouth dimple blendshapes at various timepoints throughout the expression. Alexithymia was a significant negative predictor of the left and right eye squint blendshapes at the start and end of the expression, and of the mouth pucker and mouth funnel blendshapes near the start of the expression (see Figure 7.9).

Figure 7.9.

Graphs showing the t-values for the significant group (top) and alexithymia (bottom) effects on activation across blendshapes and time for sad spoken expressions.



Note. Positive values (e.g., orange, red) signify higher activation in the autistic participants or a positive predictive relationship between activation and alexithymia. Negative values (e.g., blue and purple) signify lower activation in the autistic participants or a negative predictive relationship between activation and alexithymia. This graph also features heatmaps to help readers visualise the significant effects. The heatmaps show the significant differences at 0.8 second intervals (48 frames).

Activation across the time-course of spoken expressions: Summary

For spoken expressions of anger, the autistic participants (compared to non-autistic participants) exhibited reduced activity in the eye and eyebrow region, and increased activity around the mouth. For happiness, the autistic participants exhibited reduced activation around the eyes, eyebrows, and cheeks which, as with posed expressions, suggests a smile that is constrained to the mouth region. There were also differences in configuration at this mouth region for these expressions, with the autistic participants puckering and funnelling their mouth more, but smiling, shrugging and rolling their mouth less when speaking in a happy fashion. Similarly, for sad spoken expressions, the autistic participants displayed a different mouth configuration to their non-autistic peers, placing great emphasis on moving the upper lip up, and lower emphasis on pulling the corners of their mouth down (at specific timepoints).

Individuals high in alexithymic traits tended to activate blendshapes associated with anger when posing happiness and vice versa, suggesting less differentiation between angry and happy expressions. For sadness, alexithymia was associated with alterations to the activity around the mouth region at various timepoints in the expression.

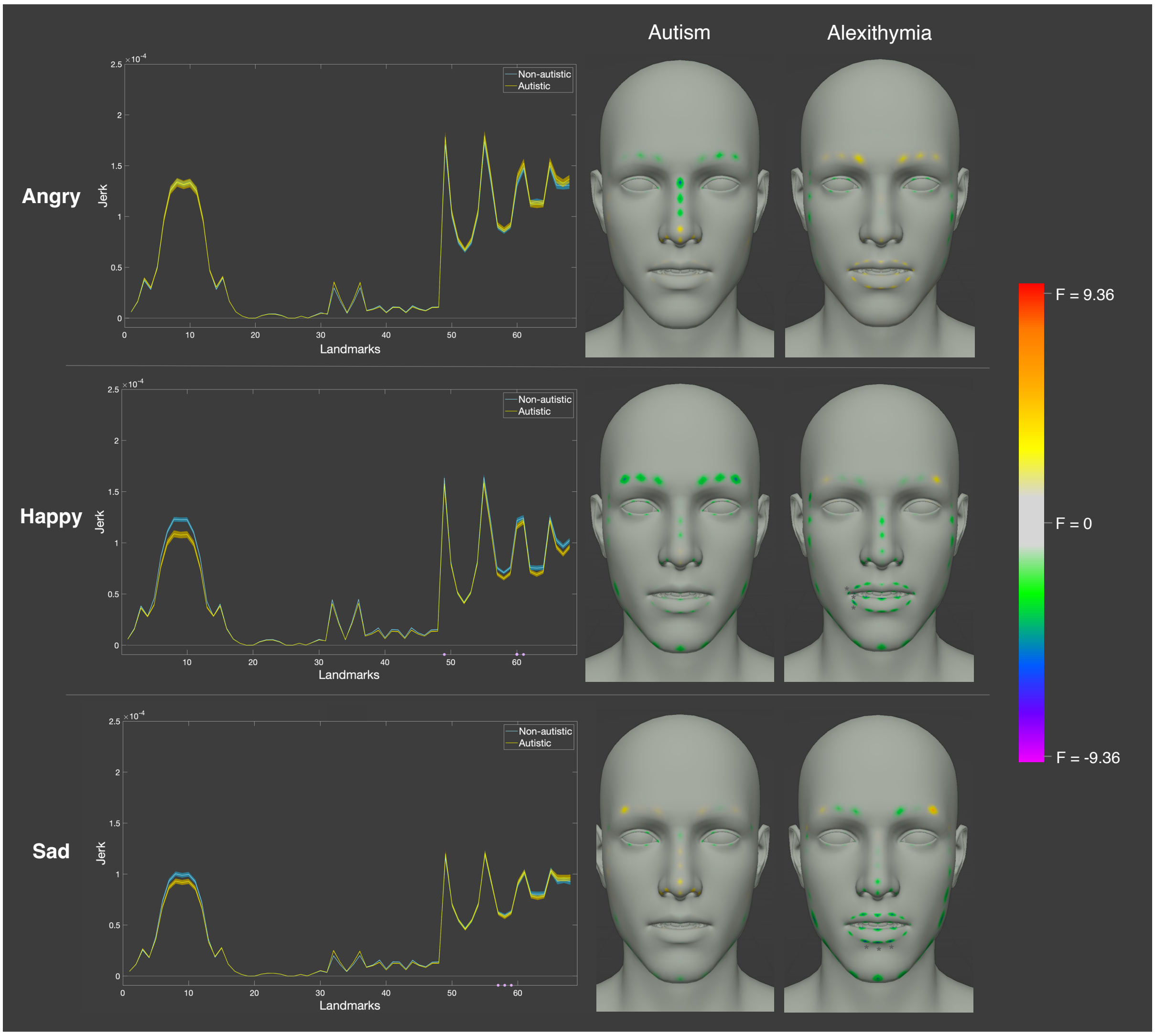
Jerk averaged across the whole time-course of spoken expressions

Finally, we aimed to determine whether there were significant group differences in the jerkiness of spoken expressions across the emotions. To fulfil this aim, we took an average of jerk across all timepoints in the recording for each landmark, participant, and repetition, for each of the emotions respectively. Following this, for each of the 68 landmarks, we conducted a linear mixed effects model of jerk as a function of group and TAS scores, with subject and repetition as random intercepts (816 datapoints for each model) for each of the emotions. As previously, we conducted a permutation test on the data to account for multiple testing (see above).

Our analysis revealed that there were no significant group differences in the jerkiness of movements for angry, happy or sad spoken expressions at any of the facial landmarks. Similarly, alexithymia did not predict jerk at any of the facial landmarks for angry expressions. However, for happiness and sadness, alexithymia was a negative predictor of jerk at specific mouth facial landmarks [happiness: 15% landmarks; mean significant $F = -4.41$; sadness: 15% landmarks, mean significant $F = -4.45$; see Figure 7.10].

Figure 7.10.

Graphs showing the jerkiness of spoken angry (top), happy (middle) and sad (bottom) autistic (orange) and non-autistic (blue) facial movements across facial landmarks.



Note. In the left panel, facial landmarks where there are significant group differences are shown in green, and facial landmarks where alexithymia contributes to jerk are shown in lilac. In the right panel, the F values for the group and alexithymia effects at each facial landmark are shown. Positive values (e.g., yellow, orange, red) signify higher jerk in the autistic participants or a positive predictive relationship between jerk and alexithymia. Negative values (e.g., green, blue and purple) signify lower jerk in the autistic participants or a negative predictive relationship between jerk and alexithymia. Stars denote statistical significance at $p < .05$.

Jerk averaged across the whole time-course of spoken expressions: Summary

There were no differences between autistic and non-autistic individuals in the jerkiness of movements for angry, happy or sad spoken expressions. Alexithymia, however, was associated with less jerky mouth movements for both happiness and sadness.

Posed and spoken expressions: Overall summary

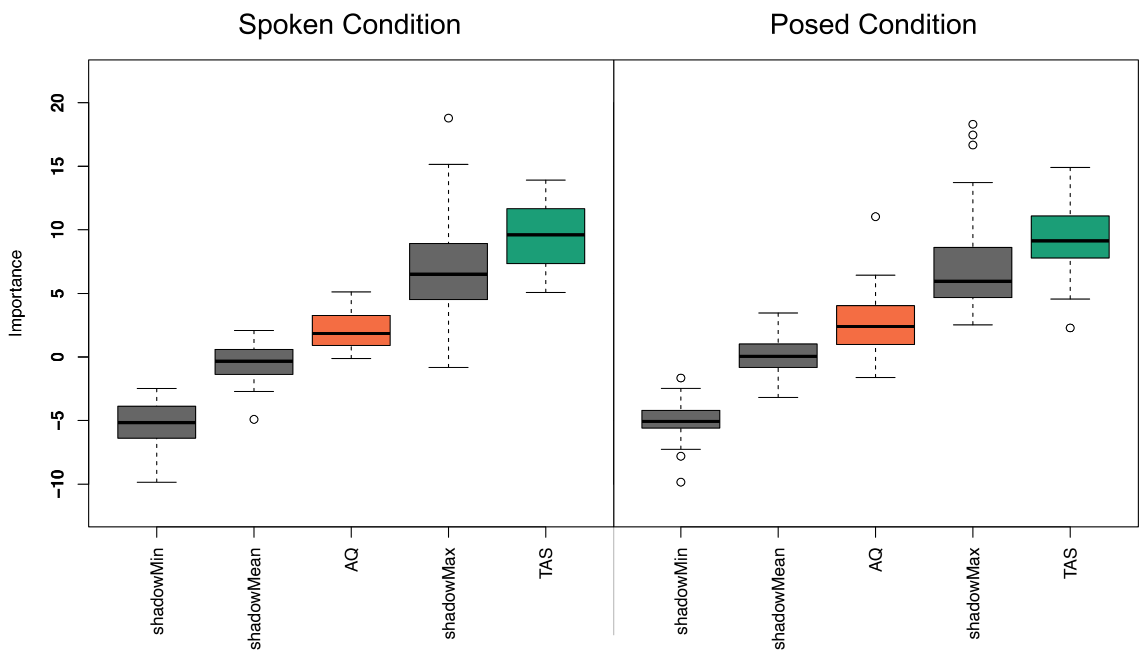
Across both the posed and spoken conditions, autistic participants tend to communicate anger more with the mouth rather than the eye and eyebrows. Across both conditions, the autistic participants displayed lower activation of the eye, eyebrow, and cheek region suggesting that the smile does not "reach the eyes" as much as for non-autistic participants. For both posed and spoken conditions, the autistic participants tended to make a downturned expression by raising their upper lip more than their non-autistic peers. In contrast, alexithymic expressions were characterised by greater similarity between anger and happiness.

The differentiation of angry and happy facial expressions: Exploratory Analysis

As discussed previously, the results from our primary analyses raise the possibility that those high in alexithymia produce less differentiated angry and happy facial expressions than those low in alexithymia, even after accounting for autism. That is, we found that individuals high in alexithymia displayed elevated activation of the mouth smile blendshapes when posing anger, and the mouth frown blendshape when posing happiness (relative to those low in alexithymia). Thus, to formally test the contribution of autism and alexithymia to the differentiation of angry and happy spoken expressions, we conducted an exploratory random forests analysis[431], using the Boruta[432] wrapper algorithm (as described in [426,427,473]; see Chapter 5). In this analysis, alexithymia was deemed important [Mean Importance Score (MIS) = 9.59], and autism was deemed unimportant [MIS = 2.13], for the differentiation of angry and happy *spoken* expressions (see Figure 7.11, left). A follow-up analysis identified the same pattern of results in the posed condition (alexithymia [MIS = 9.36]; autism [MIS = 2.64]; see Figure 7.11, right). In sum, these results suggest that alexithymia, and not autism, is associated with lower differentiation of angry and happy facial expressions across both posing conditions.

Figure 7.11.

Random forest importance scores for AQ and TAS to the differentiation of spoken (left) and posed (right) angry and happy expressions.



Note. Variable importance scores displayed as boxplots. Box edges correspond to the interquartile range (IQR); whiskers represent 1.5 × IQR distance from box edges; circles denote outliers. Box colour reflects the decision made by the algorithm: Green = confirmed important, yellow = tentative, red = rejected; grey = shadow features – shadowMin, shadowMean, shadowMax (minimum, mean and maximum variable importance scores of shadow features, respectively).

7.3.3. The link between production and perception

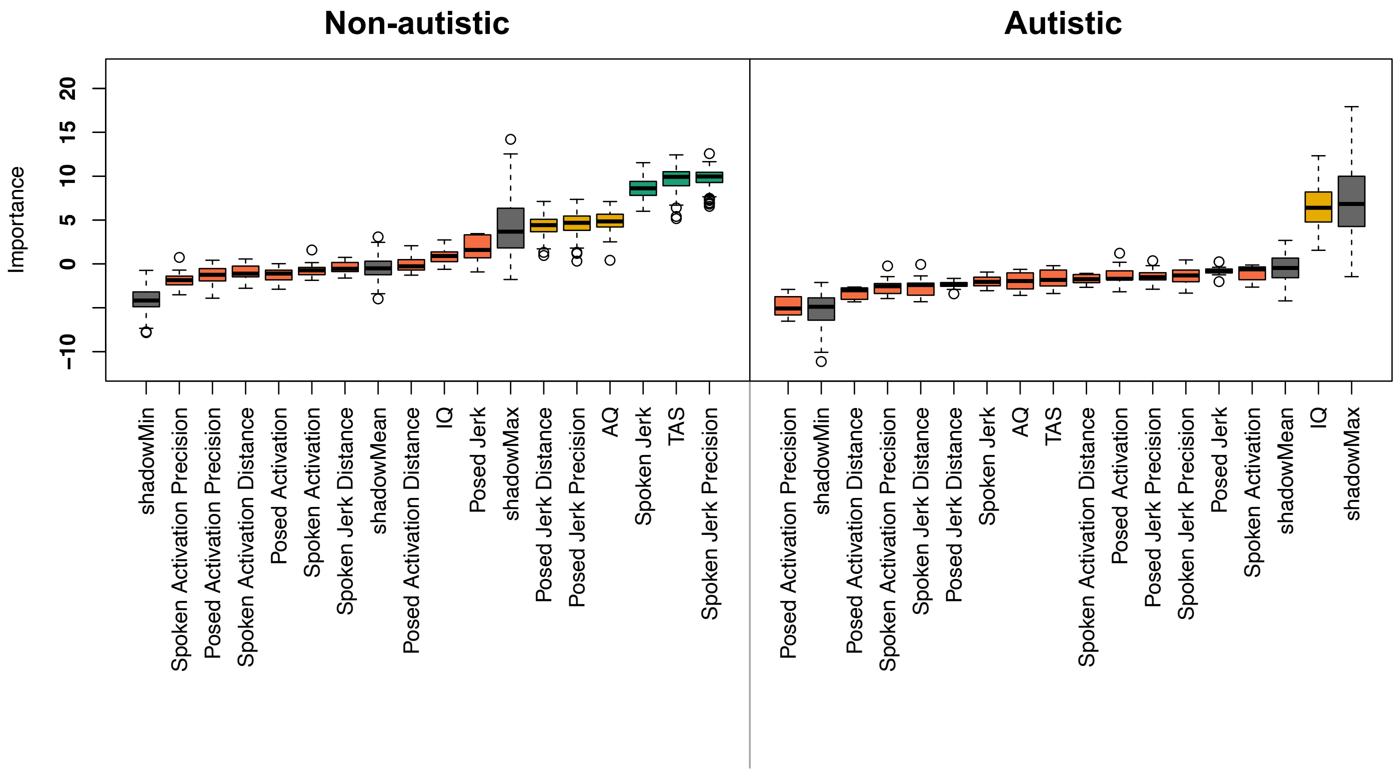
Subsequently, we aimed to investigate whether features of emotion-production contribute to emotion perception which we operationalised as emotion recognition accuracy. Building on the body movement and emotional experience literatures we predicted that more jerky, and less precise and/or differentiated, expressions would be associated with reduced emotion recognition accuracy. We explored whether this was the case for both autistic and non-autistic individuals by conducting a random forests analysis[431] separately for each group, using the Boruta[432] wrapper algorithm (version 7.7.0; as in [426,427,473]). To test our predictions, we included emotion recognition accuracy as the outcome variable: feature variables included mean jerk, mean jerk precision, mean jerk distance (i.e., differentiation) for both posed and spoken expressions; mean activation, mean activation precision, mean activation distance (i.e., differentiation) for both posed and spoken expressions; plus AQ and TAS.

For the non-autistic participants, of the 15 variables tested, three were classified as important, three as tentatively important, and nine were deemed unimportant for emotion recognition. Figure 7.12 (left) shows that spoken jerk precision [Mean Importance Score (MIS) = 9.75], TAS score [MIS = 9.54] and mean spoken jerk [MIS = 8.61] were classed as important for emotion recognition. AQ [MIS = 4.81], posed jerk precision [MIS = 4.61] and posed jerk distance [MIS = 4.37] were tentatively important for non-autistic emotion recognition. All other variables were deemed unimportant. Notably, here we found that variables corresponding to the spoken condition were deemed important for emotion recognition, while those in the posed condition were deemed tentatively important. This finding is expected; participants should be more likely to draw on their own spoken productions since the stimuli in the emotion recognition task also comprise spoken expressions.

For the autistic participants, of the 15 variables tested, one was classified as tentatively important, and 14 were classified as unimportant for emotion recognition. As shown in Figure 7.12 (right), IQ was deemed tentatively important [MIS = 6.35] and all other variables were deemed unimportant for autistic emotion recognition.

Figure 7.12.

Random forest variable importance scores for non-autistic (left) and autistic (right) emotion recognition.



Note. Variable importance scores for all 15 variables included in the Boruta random forest regression model, displayed as boxplots. Box edges correspond to the interquartile range (IQR); whiskers represent 1.5 × IQR distance from box edges; circles denote outliers. Box colour reflects the decision made by the algorithm: Green = confirmed important, yellow = tentative, red = rejected; grey = shadow features – shadowMin, shadowMean, shadowMax (minimum, mean and maximum variable importance scores of shadow features, respectively).

Following this, to verify the results from our random forests analyses, we conducted a linear regression in each group, predicting mean emotion recognition accuracy with the "important" and "tentatively important" variables. In these regressions, we added the predictor variables sequentially, starting with the variables with the highest mean importance scores, until there was no longer a significant improvement to the model.

For autistic individuals, IQ was a significant positive predictor [$t = 2.60$, $b = 0.48$, $p = .016$], accounting for 22.6% of the variance in emotion recognition accuracy, and significantly improving the model [F change = 7.73, $p = .016$, R^2 change = 22.6%]. Bayesian analyses demonstrated that there was moderately strong evidence for this model relative to a null model [$BF_{10} = 3.62$, $R^2 = 22.6\%$].

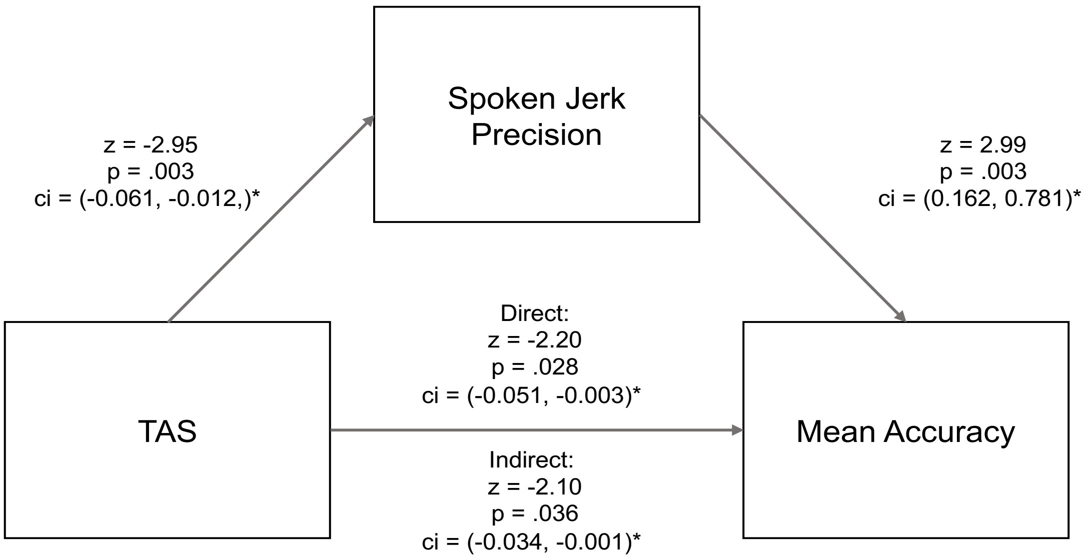
For non-autistic individuals, entering mean spoken jerk precision as a predictor of emotion recognition significantly improved the model [F change = 16.59, $p < .001$, R^2 change = 41.9%], accounting for 41.9% of the variance. Adding TAS score in the second step marginally improved the model [F change = 4.27, $p = .051$, R^2 change = 9.9%], accounting for an additional 9.9% of the variance. There were no further improvements to the model when we added the remaining important and tentatively important variables. In the final model, mean spoken jerk precision [i.e., consistency in the jerkiness of emotional expressions; $t = 2.80$, $b = 0.48$, $p = .010$, R^2 change = 41.9%] was a significant positive predictor of emotion recognition accuracy. Alexithymia approached significance as a negative predictor of emotion recognition accuracy [$t = -2.07$, $b = -0.35$, $p = .051$]. Bayesian analyses demonstrated that there was very strong evidence for our final model relative to a null model for non-autistic individuals [$BF_{10} = 87.55$, $R^2 = 51.4\%$]. In contrast, the same analysis demonstrates moderate evidence for the null model for autistic individuals [$BF_{10} = 0.22$, $R^2 = 2.4\%$].

The link between production and perception: Exploratory analyses

The above analysis implicated spoken jerk precision in emotion recognition within the *non-autistic* group. To gain insight into individual differences that might be related to higher jerk imprecision in the non-autistic population we conducted a further exploratory analysis wherein we tested the contribution of various demographic factors to spoken jerk precision in the non-autistic group. That is, we constructed a Bayesian linear regression model predicting spoken jerk precision with age, IQ, AQ and TAS. The strongest model included only TAS as a predictor [BF_{10} = 5.44, R^2 = 25.0%]: those higher in alexithymic traits typically displayed less precise (i.e., more variable) facial expressions in terms of jerk [t =-2.83, *b* = -0.50, p = .009]. Building on this we conducted an exploratory mediation analysis to test the hypothesis that alexithymia might exert an indirect effect on emotion recognition by influencing spoken jerk precision. This analysis revealed that there were both significant direct [z = -2.20, p = .028, 95% CI = (-0.051, -0.003)] and indirect [z = -2.10, p = .036, 95% CI = (-0.034, -0.001)] effects of alexithymia on emotion recognition accuracy (see Figure 7.13). Hence our findings suggest a potential causal direction: for non-autistic individuals, being high in alexithymic traits may lead to more variable productions of emotional facial expressions, which in turn may result in poorer emotion recognition accuracy.

Figure 7.13.

Mediation models showing the contribution of alexithymia to non-autistic emotion recognition via spoken jerk precision.



Note. The asterisks (*) denote statistical significance based on 95% confidence intervals.

7.4. Discussion

In the current study, we first compared the facial expressions produced by autistic and non-autistic individuals, after controlling for differences in facial morphology and alexithymia, and second, explored whether the jerkiness, activation profile, precision, and differentiation of participants' own emotional expressions contributed to their ability to recognise others'. Our results suggest that both autism and alexithymia contribute to levels of activation and jerk when producing emotional expressions. Notably, however, these contributions differed as a function of the displayed emotion (i.e., across anger, happiness and sadness), the facial action unit (e.g., brow down blendshapes, mouth smile blendshapes, etc.), and the posing condition (i.e., posed versus spoken). That is, the autistic participants (relative to non-autistic participants) did not exhibit consistently higher or lower activation, or higher or lower jerk, across all facial features, for all emotions. This evidence points to differences in both the configuration and kinematics of facial features (i.e., relative activation of features) between autistic and non-autistic individuals when expressing emotion. Such differences could, at least partially, explain why non-autistic individuals find it difficult to recognise the emotions of autistic people, and vice versa (e.g., [147,534]; though see [267]).

For anger, both when posing and speaking, the autistic participants displayed lower activation of the brow down blendshapes, and higher activation of specific mouth blendshapes (e.g., mouth frown, mouth upper up), than their non-autistic peers (even after minimising effects of differences in facial morphology and controlling for alexithymia). Autistic individuals also displayed significantly higher jerk for all mouth facial landmarks in the posing condition. Together, this evidence suggests that autistic participants may rely more on the mouth, and less on the eyebrow region, to signal anger than their non-autistic counterparts, both during posed and spoken emotional expressions. Interestingly, autistic individuals typically attend more to the mouth, and less to the eye region (than their non-autistic peers), when *recognising* emotional expressions (e.g., [224-226]; though also see [359]). One possible explanation that develops from our current findings is that, since autistic individuals rely more on the mouth, and less on the eyebrows, (relative to non-autistic individuals) to signal anger themselves, these participants may expect there to be more expressive information in the mouth region, and thus attend to this area more. Such attentional biases could then lead to downstream difficulties recognising anger since the majority of the expressive information is thought to be displayed in the upper half of the face[227,228]. Further research is necessary to test whether differences between groups in the *production* of emotional facial expressions contribute to differences in the *sampling* and *recognition* of them.

For happiness, there were numerous, and large, differences between groups in activation for both posed and spoken expressions, even after minimising the effects of differences in facial morphology and controlling for alexithymia. Specifically, we found that the autistic participants displayed significantly lower activation of many blendshapes typically associated with happiness in both conditions – the left and right mouth smile, cheek squint, eye squint, and brow down blendshapes. By contrast, we found that the autistic participants exhibited higher activation for other cheek and mouth blendshapes (e.g., mouth funnel, mouth pucker, cheek puff, mouth roll upper) in both conditions. Together, these results suggest there are group differences in mouth configuration when expressing happiness, with autistic individuals displaying a less exaggerated, and more puckered, smile. In addition, our results suggest that the autistic participants may rely more on the mouth to signal happiness, and less on the eyes, eyebrows and cheeks (similar to above for anger; see Figure 1 and Figure 6 for visual representation). This may explain why autistic expressions have been rated as less natural in previous experiments (e.g., [265]): in the neurotypical literature, genuine (i.e., natural) happy expressions (i.e., "Duchenne smiles") are said to be characterised by activation of *both* the zygomaticus major muscle – which pulls the lip corners upwards (i.e., mouth) – and the orbicularis oculi muscle – which lifts the cheeks, gathers the skin around the eye, and pulls the brow down – while non-genuine happy expressions only involve the former (e.g., [535-538]). Hence, the happy expressions produced by autistic individuals may be perceived as less genuine or natural (by non-autistic observers), as they only involve activation of the zygomaticus major muscle (i.e., the mouth). Notably, although these expressions may be perceived as less genuine based on neurotypical criteria, this does necessarily mean that autistic individuals actually produce less authentic expressions (i.e., more contrived or forced expressions). Rather, it could be the case that genuine expressions of happiness for autistic individuals do not involve the orbicularis oculi muscle to the same extent as for non-autistic individuals. Further work is necessary to characterise genuine and posed autistic facial expressions, and to ascertain whether autistic expressions are rated as less natural or atypical in appearance (e.g., [263,265,266,278]) due to lower activation of the cheek squint, eye squint, and brow down blendshapes.

For sadness, there were fewer group differences in activation (relative to anger and happiness), and no group differences in jerk, after minimising the effects of differences in facial morphology and controlling for alexithymia. In the posed condition, we identified that the autistic participants exhibited significantly lower activation of the jaw forward blendshape when at peak expression, and higher activation of the mouth upper up blendshape when moving into the expression. In the spoken condition, while the autistic participants displayed significantly lower activation of the mouth frown, mouth roll and eye squint blendshapes (at specific moments in time), these participants showed elevated activation of the mouth upper up, brow outer up, and jaw left blendshapes. Thus, once again, our results point to different configurations (i.e., relative activation) of facial features for both posed and spoken sad expressions between groups. Most notably, the autistic participants tended to raise their upper lip more (posed and spoken condition), and pull the corners of their mouth down less (spoken condition), to display the downturned mouth that is characteristic of a sad expression (relative to their non-autistic peers).

The results of the current study partially support our hypothesis concerning the jerkiness of facial movements. Since previous studies have found that autistic individuals exhibit jerkier whole-body, upper-limb and head movements (e.g., [512-516]), we predicted that autistic participants in the current study would display significantly more jerky facial expressions than their non-autistic counterparts. However, whilst we found that the autistic participants (relative to non-autistic participants) exhibited higher jerk at all mouth facial landmarks for posed expressions of anger, thus supporting our hypothesis, we also found lower jerk at specific eyebrow landmarks for happiness, and no differences in jerk for sadness, thus contradicting our hypothesis. Moreover, we found that there were no significant differences in jerk between autistic and non-autistic participants in the spoken condition. When interpreting these results, it is important to consider the relationship between activation and jerk. By doing so, we can attempt to explain why we see different jerk effects across emotions. Here, for anger, we found differences between the groups in terms of jerk that were not mirrored in activation: when averaging across timepoints, the autistic participants displayed greater jerk, but not activation, in the mouth region when posing angry expressions. These results suggest that the autistic participants may have exhibited comparable levels of activation of the mouth, but reached these levels in a more jerky fashion. For happiness, on the other hand, differences between the groups in the jerkiness of movement were mirrored in terms of activation for the eyebrow region: the autistic participants displayed lower activation of the brow down blendshape, and lower jerk for eyebrow landmarks when posing happiness. Thus, the autistic participants may have displayed lower jerk for happiness *because* they activated, and thus moved, this region to a lesser extent. Future investigations should aim to determine the significance and (in)dependency of the group effects on jerk and activation for angry, happy and sad emotional expressions.

In the current study, we found that alexithymia significantly contributed to the production of emotional facial expressions, both in terms of activation and jerk. For example, we found that alexithymia, and not autism, was associated with less differentiated angry and happy facial expressions (in terms of activation) for both posed and spoken expressions. Specifically, in the spoken condition, we found that individuals high in alexithymia displayed elevated activation of the mouth smile blendshapes when posing anger, and the mouth frown blendshape when posing happiness (relative to those low in alexithymia). Concurrently, for both posed and spoken expressions, we found that there were smaller differences (i.e., smaller distances) in activation between angry and happy facial expressions across blendshapes for those high, relative to low, in alexithymia. These results suggest that highly alexithymic individuals may produce more overlapping, and thus ambiguous, angry and happy facial expressions. Notably, previous work, which has not controlled for alexithymia, has suggested that autistic individuals display less differentiated facial muscle activation for anger, happiness and fear[273], and positive and negative emotions[518]. Our results raise the possibility that these differences, which have previously been attributed to autism, may be better explained by alexithymia. Nevertheless, further research is necessary to confirm our findings, and to assess whether alexithymia contributes to greater overlap between facial expressions for other emotions (e.g., anger and disgust, surprise and fear, etc.). Further research might also question whether observers struggle to recognise the less differentiated facial expressions produced by individuals who are high in alexithymic traits.

Relatedly we also found that, for non-autistic individuals, those high in alexithymia typically produced less precise (i.e., more variable) facial expressions with respect to jerk (in the spoken condition). There are a number of potential explanations for this finding. Since alexithymia is linked to proprioceptive differences[520-522] and proprioception is essential for motor control[523-526], one explanation is that highly alexithymic individuals have lower control of their movements, thus resulting in more variable productions of facial expressions across instances. Another possibility is that alexithymic individuals are less able to draw on their own concepts or experiences of emotion when attempting to pose the expressions, thus resulting in more variable productions. This is plausible since research has suggested that individuals who are high in alexithymic traits tend to have difficulties retrieving emotional information and memories (e.g., see [539]). Supporting these explanations, here we found that, when asked to report how difficult they found it to pose the emotional expressions on a scale from one to ten, those high in alexithymic traits typically reported greater difficulties [$r = 0.58$, $p < .001$]. Further research is necessary to explore whether inconsistency in the jerkiness of expressions in the alexithymic population is linked to differences in proprioception/motor control and/or access to emotional-related information.

Another key aim of this study was to assess whether there were any links between the production and perception of emotional facial expressions for autistic and non-autistic individuals. Leveraging the body movement and emotional experience literatures we predicted that more jerky, and less precise and/or differentiated, facial expressions would be associated with reduced emotion recognition accuracy. We found that precision was an important contributor for non-autistic individuals, accounting for 41.9% of the variance in emotion recognition accuracy: those who produced highly variable spoken expressions (in terms of jerk) typically had poorer accuracy on an independent task that required the recognition of emotion from motion cues. In a further exploratory analysis, we also identified that, for non-autistic individuals, alexithymia exerted an indirect effect on emotion recognition accuracy by negatively influencing the precision of spoken expressions (which in turn contributed to accuracy). Thus, these findings illuminate a potential mechanistic pathway by which alexithymia contributes to emotion recognition: having difficulties identifying and describing one's own emotions (i.e., alexithymia), may lead to more variable productions of emotional expressions, which may in turn lead to greater emotion recognition difficulties. Since structural equation modelling cannot definitively determine causality[433], future studies employing causal manipulation are necessary to test this pathway.

The current findings complement ideas proposed in template-matching models of emotion recognition. Such models posit that, to recognise the emotions of others, individuals compare incoming facial expressions to stored 'templates', which comprise the average of all previous encounters (e.g., an average angry expression across instances)[108-111]. Here, we add to this literature by demonstrating that, in addition to drawing on templates based on others' expressions (i.e., visual representations), individuals may also draw on their *own* facial expressions. Further work is necessary to unpack whether this information about own expressions relates to stored visual representations (e.g., from watching one's own expressions in the mirror) or stored motoric representations. Furthermore, our results show the utility of considering approaches like signal detection theory (SDT; see [140]) in the emotion recognition field. That is, we found that precision, an important concept in SDT, is also important with respect to emotion recognition: precise (i.e., consistent or reliable) productions of facial expressions facilitate enhanced emotion recognition. One may question why we did not find a significant effect of distance between facial expressions (differentiation) on emotion recognition. It may be that the expressions that we examined are perceptually dissimilar, and thus instances of overlap between the signal and noise distributions are relatively uncommon, leading to no effect of distance. Independent of this, there could conceivably be an effect of the precision of one's own facial expressions on emotion recognition. Here, precision may be proxy for the clarity of one's motoric representations, which could affect emotion recognition irrespective of perceptual overlap. Moreover, the expectation literature would predict that more precise (motoric) representations of incoming expressions (i.e., priors) would result in enhanced emotion recognition accuracy (see [434-437]). Future research should aim to include other emotions (e.g., surprise, disgust and fear) that share perceptual features with anger, happiness and sadness in order to identify whether an effect of the differentiation of facial expressions emerges.

While we found that the precision of spoken productions predicted emotion recognition for non-autistic individuals, no production-related factors contributed to emotion recognition for autistic individuals. When we explored demographic factors, IQ was the only significant contributor for autistic individuals, explaining 22.6% of the variance in accuracy. These results add to a growing literature suggesting that different psychological mechanisms are involved in autistic and non-autistic emotion recognition (e.g., [246,426,427]). Within this literature, there is evidence that the precision of *visual emotion representations* (i.e., the way one pictures others' emotional expression in the mind's eye) contributes to emotion recognition accuracy for non-autistic individuals, but not autistic individuals (e.g., [426,473]). Taken together, these studies suggest that autistic individuals may not be using their visual representations and productions of facial expressions (or, at least, use them to a lesser extent than non-autistic individuals) to help them recognise others' emotions. This idea aligns well with Bayesian theories of autism which propose that, compared to non-autistic people, autistic individuals are less influenced by prior expectations (e.g., [259-261]).

If autistic individuals rely less on stored visual representations and productions of facial expressions, *how* are they recognising other people's emotions? One plausible explanation is that autistic individuals have developed cognitively or verbally mediated compensatory strategies[256,257]. For example, they may follow a "rule-based" strategy where they assess the extent to which an incoming expression matches a list of features they have learnt to be associated with different emotions (e.g., anger: "furrowed eyebrow"; happiness: "lips raised"; sadness: "downturned mouth")[256,257]. If autistic individuals are employing these cognitively or verbally mediated rule-based strategies, then we might expect emotion recognition performance to be related more to verbal or cognitive ability in the autistic than non-autistic group. Supporting this idea, here we found that IQ was a significant predictor of emotion recognition for the autistic [$F(1,23) = 6.73$, $p = .013$, $R^2 = 22.6$], but not non-autistic participants [$F(1,23) = 2.62$, $p = .120$, $R^2 = 10.2\%$]. Concurrently, if autistic individuals are employing more effortful strategies, rather than automatically comparing to their visual representations or productions, this could explain the longer emotion recognition response latencies found for autistic individuals (e.g., [229-238]). Further research is necessary to test whether autistic people adopt a rule-based strategy to recognise others' emotions, and to identify what other factors contribute to autistic emotion recognition.

Limitations and Future Directions

Although the results of the current study are highly informative with respect to understanding the differences in the facial expressions produced *voluntarily* by autistic and non-autistic individuals, further work is necessary to characterise and compare spontaneously produced expressions. Here, we focused specifically on voluntary expressions, which are ubiquitous in everyday life, posed in order to deliberately communicate one's thoughts, intentions, and emotions to interaction partners. However, it is important to note that spontaneous expressions are also common in day-to-day life, may comprise more accurate indicators of an individual's emotions (e.g., [540]), and may differ in appearance to posed expressions[541-543]. As such, the findings documented here may not generalise to spontaneously produced emotional expressions. Therefore, further work is necessary to test the contribution of autism and alexithymia to the spatiotemporal and kinematic properties of spontaneous emotional facial expressions.

It is also important to address the limitations of our study with respect to generalizability. Given that the participants in our sample were predominantly white (82.35%; see Appendix 6.2), and from Western Cultures, our results may not be representative of those from other racial, ethnic, or cultural backgrounds. This is particularly relevant here as previous studies have found that visual representations and productions of emotion vary across cultures (e.g., [388,389,462,464]). For example, one study found that (non-autistic) individuals from Western cultures tended to emphasise the eyebrows and mouth in their visual representations, while those from East Asian cultures tended to emphasise expressive information in the eye region[388]. As such, the Western (non-autistic) participants involved in the current study may have displayed greater activation of the eyebrow and mouth in their facial expressions, relative to what would be seen with East Asian participants. Furthermore, since we found that the autistic participants tended to exhibit lower activation of eyebrow and mouth regions when posing specific emotional expressions (e.g., happiness), it may be that differences between autistic and non-autistic people in facial expressions are smaller in East Asian cultures. Alternatively, it could be that these group differences are consistent across Western and East Asian cultures, due to both autistic and non-autistic individuals in East Asian cultures showing comparably lower activation of these regions relative to their Western peers (thus maintaining the difference between groups). Further research is necessary to characterise and compare the facial expressions of autistic and non-autistic people across cultures.

Chapter 8: General Discussion

8.1. Overview of findings

In this project, across six empirical chapters, I have developed novel experimental paradigms to assess the conceptualisation, experience, visual representation, production, and recognition of emotion in autism, and created new, mathematically plausible, mechanistic models which shed light on the processes involved in emotion recognition for *both* autistic and non-autistic people. In doing so, I have provided significant methodological and theoretical contributions to the literature, and addressed a number of limitations of previous research.

Prior to this project, the majority of studies investigating emotion-processing in autism had not controlled for alexithymia – a subclinical condition highly prevalent in the autistic population[199] theorised to be responsible for autistic individuals' difficulties with emotions[207]. As such, one of the primary aims of this project was to determine whether there are differences between autistic and non-autistic individuals in the conceptualisation, experience, visual representation, production, and recognition of emotion, after controlling for this important confound. In sum, our results suggest that there are no differences between groups in the understanding or differentiation of emotion concepts (Chapter 6), the precision or differentiation of emotional experiences (Chapter 6), and the speed (Chapter 3) or differentiation of visual emotion representations (Chapter 5), after controlling for alexithymia. Nevertheless, I did find differences between groups in the precision of visual representations (Chapter 5), the production of emotional facial expressions (Chapter 7), and the recognition of specific emotions (Chapter 2), even after accounting for this confound. As such, alexithymia may underlie some, but not all, of the differences between autistic and non-autistic people in emotion-processing.

Despite long-standing suggestions that autistic individuals adopt alternative strategies to read the emotions of others (e.g., [256, 257]), at the onset of this project, very few studies had compared the mechanisms underpinning emotion recognition for autistic and non-autistic people. Therefore, another principal aim of this project was to characterise and compare the mechanisms involved in emotion recognition for these groups. Here I found evidence for similarities and differences in the processes involved, and constructed theoretical, mechanistic models of, autistic and non-autistic emotion recognition (see section 8.6.2 for a full discussion).

Throughout the remainder of the discussion, I synthesise these findings with existing literature, reflect on general strengths and limitations of this project (see Chapters for more specific limitations), and outline future research directions to explore outstanding questions.

8.2. The conceptualisation and experience of emotion in autism

Prior to this project, a limited body of work had assessed the understanding, conceptualisation, and experience of emotion in autism. However, as highlighted in Chapters 1 and 6, such previous research had rarely employed objective methods to assess these constructs, and those that had, did not control for alexithymia. As such, at the onset of this project there were limited objective tools, and it was unclear whether differences in the understanding, conceptualisation and experience of emotion in autism were underpinned by co-occurring alexithymia (as suggested by the alexithymia hypothesis[207]). To remedy these limitations, in Chapter 6, I compared the performance of autistic and non-autistic adults on a series of objective, emotion-based, tasks that I developed after controlling for alexithymia. Despite being sufficiently powered to detect small-moderate effects, I found that there were no differences between groups in their ability to understand or differentiate semantic emotion concepts, nor any differences in the precision or differentiation of emotional experiences, after controlling for alexithymia. These results contradict previous findings suggesting that autistic individuals are less able to differentiate semantic concepts and experiences of emotion[148]. This disparity could arise due to the fact that I controlled for alexithymia or that I employed a task that did not require labelling of emotional state, in contrast to the previous study conducted by Erbas and colleagues (wherein participants rated their responses on numerous emotion rating scales)[148]. Alternatively, this discrepancy may be caused by differences in sample demographics between studies; our study involved adults whilst the previous study involved adolescents. Thus, autistic individuals may struggle to differentiate experiences and semantic concepts of emotion relative to their non-autistic counterparts during adolescence, which disappear as they transition into adulthood. To test this possibility, future studies should employ our EmoMap paradigm, which is less confounded by language ability than previous methods[450], to assess the emotion differentiation performance of autistic and non-autistic children and adolescents, while controlling for the influence of alexithymia. Such work could allow researchers to determine under what conditions and tasks autistic people display difficulties with emotion differentiation.

My finding that neither autism nor alexithymia predicted emotional precision contradicts the previous results (from Huggins et al[292]) suggesting that the level of alexithymic, but not autistic traits, contributes to the precision of emotional experiences[292]. There are also multiple potential explanations for this discrepancy. Firstly, the task employed by Huggins et al[292] assessed emotional precision for positive (i.e., “pleasing”) and negative (i.e., “upsetting”) affective states, whereas here I indexed emotional precision for discrete emotions. As such, it is possible that those high in alexithymia have lower precision when evaluating the valence of their affective experiences, but intact precision when evaluating whether these experiences map on to discrete emotion labels. Secondly, Huggins and colleagues[292] selected images associated with varied valence, but constant arousal levels, whereas the images employed here varied across both dimensions. Consequently, those high in alexithymia may struggle to evaluate which image evokes a stronger emotional response when this judgement is solely based on valence (i.e., when arousal is fixed at a constant), and not when it can be based on *both* valence and arousal (i.e., when both valence and arousal vary). Further research is necessary to formally test these possibilities.

8.3. Visual representations of emotion in autism

As highlighted in Chapter 1, the results from previous studies (e.g., [147,222,240,256,257]) have led researchers to *indirectly* infer that visual emotion representations may be atypical in autism. Specifically, prior to this project, previous work had found differences in the production of emotional facial expressions[147], the appraisal of highly exaggerated stimuli[256,257], and in identification thresholds [222,240], indicating that there *may* be differences in visual representations between groups. Notably, however, all previous work had specifically relied on static snapshots of faces, thus pointing towards differences in representations between groups in the spatial domain. Adding to this literature, in Chapter 2, I identified that autistic individuals had higher identification thresholds than their non-autistic counterparts for angry facial expressions in the kinematic domain: compared to controls, the autistic participants required a higher speed (and thus higher intensity of anger[239]) before they could accurately identify angry expressions. This evidence raised the possibility that autistic and non-autistic individuals have different visual emotion representations, with the former possessing more caricatured angry representations with respect to speed. However, further research, which directly examined visual emotion representations, was necessary to test this possibility.

Therefore, in Chapter 3 I asked autistic and non-autistic individuals to adjust the speed of angry, happy and sad expressions until they matched their visual representations for these emotions. In conflict with our hypothesis, I found no differences between groups in the speeds attributed to angry, happy and sad facial expressions across both full-face and partial-face conditions, in all statistical analyses. Thus, our results suggest that autistic and non-autistic individuals do not have different visual representations of angry, happy and sad facial expressions in terms of speed (at least for point-light displays; see Chapter 8.7). As highlighted in Chapter 3, further research is necessary to determine whether there are differences in the visual representations of autistic and non-autistic individuals in the spatial domain. Such work could follow similar methods to those used here (e.g., method of adjustment[284]), or reverse correlation techniques (e.g., [384,388,389,463-465]), to index and then compare such representations.

As highlighted in Chapter 1, I theorised that there could be other features of imagined representations, in addition to speed, that influence our ability to read others' emotions, such as precision and differentiation. To assess these factors, in Chapter 4, I asked participants to manipulate a dial to change the speed of numerous angry, happy and sad expressions until they matched their visual representation for these emotions. The precision of visual representations was calculated based on the variability in the speeds attributed to the same emotional expression, while differentiation was calculated based on the absolute difference in the speeds attributed to distinct emotions. In Chapter 4, I confirmed an involvement of precision in emotion recognition for non-autistic individuals (see section 8.6 for a full discussion), thus illuminating a potential candidate mechanism that may underpin emotion recognition difficulties in autism (e.g., difficulties recognising anger[147, 219-223]). Therefore, in Chapter 5 I compared autistic and non-autistic individuals with respect to these variables. Although I found no differences between groups in differentiation, unexpectedly, I found that the autistic participants had more precise visual emotion representations even after controlling for alexithymia. Notably, however, this enhanced precision did not confer any benefit for their emotion recognition performance: there were no differences between groups in this ability, and the precision of representations did not contribute to emotion recognition for autistic individuals. In sum, these results suggest that autistic individuals have more precise visual emotion representations (at least in terms of speed) but are nevertheless weakly influenced by them when recognising others' emotions (see section 8.6.1 for a full discussion). As discussed in Chapter 5, further work is necessary to determine whether autistic individuals have more precise visual emotion representations with respect to other cues, such as the degree of spatial exaggeration.

8.4. Production of emotion in autism

Prior to this project, there was some evidence to suggest that there may be differences in the facial expressions produced by autistic and non-autistic individuals (see [146,150]). However, this research had failed to delineate clear expressive differences because methods with low sensitivity had been used, naturalistic forms of movement (e.g., while speaking) had been underexplored, and both facial morphology and alexithymia had not been accounted for. Therefore, in Chapter 7, I employed facial motion capture to track the facial movements of autistic and non-autistic individuals across two conditions (posed and spoken), retargeted the expressions onto avatar faces to minimise the influence of morphological differences, and modelled the contribution of both autism and alexithymia to the spatiotemporal and kinematic properties of the expressions. Specifically, I aimed to establish whether there were differences in activation between groups, thus disentangling the mixed findings in the literature: some previous studies had found increased expressivity in autism, while others had found reduced expressivity, or no differences between groups (e.g., [263,265-270,274,517]). Moreover, I aimed to test the hypothesis that the autistic participants would display significantly more jerky expressions than their non-autistic counterparts (in line with findings in the body movement[512-516]). Finally, I aimed to assess whether alexithymia, and not autism, is responsible for differences between autistic and non-autistic individuals in the production of emotional facial expressions (as suggested by the alexithymia hypothesis[207]).

In Chapter 7, I found that both autism and alexithymia contributed to the degree of activation and jerk when producing emotional expressions. Notably, however, these contributions, differed as a function of the displayed emotion, the facial action unit, and the posing condition. That is, the autistic participants did not exhibit consistently higher or lower activation or jerk across all facial features, for all emotions, than their non-autistic peers (after controlling for alexithymia). Rather, the autistic and non-autistic participants produced facial expressions that differed in appearance – varying in the relative activation of facial features (i.e., in spatial configuration) across emotions. In conflict with our hypothesis, the autistic participants did not display consistently higher jerk across all emotions and posing conditions.

Specifically, I found that for anger, both when posing and speaking, the autistic participants displayed lower activation of the brow down blendshapes, and higher activation of specific mouth blendshapes, than their non-autistic counterparts (even after controlling for alexithymia). Concurrently, the autistic participants displayed higher jerk for all mouth facial landmarks in the posing condition. As stated in Chapter 7, these results suggest that autistic individuals may rely more on the mouth, and less on the eyebrows, to signal anger than their non-autistic peers when voluntarily producing emotional expressions. For happiness, across both posing conditions, the autistic participants displayed less exaggerated smiles that did not "reach the eyes", even after controlling for alexithymia. That is, while the non-autistic participants activated both the zygomaticus major muscle – which pulls the lip corners upwards[535-538] – and the orbicularis oculi muscle – which lifts the cheeks, gathers the skin around the eyes and pulls the brow down[535-538] – the autistic participants tended to activate solely the former. Hence, the autistic participants tended to rely more on the mouth than the eyes, eyebrows, and cheek to signal happiness. For sadness, the autistic and non-autistic participants displayed different mouth configurations across both conditions. Specifically, the autistic participants tended to make their mouth appear downturned by raising their upper lip more than their non-autistic peers. In sum, our results point to group differences in facial configurations when producing voluntary expressions of anger, happiness and sadness, even after controlling for alexithymia and minimising the influence of facial morphology. Such differences could, at least in part, explain why non-autistic individuals find it difficult to recognise the emotions of autistic people, and vice versa (e.g., [147,534]; though see [267]).

Alexithymia, on the other hand, was associated with less differentiated angry and happy facial expressions (i.e., similar patterns of activation across facial action units) in both the posed and spoken condition. Such findings suggest that previous results of less differentiated facial muscle activation for anger, happiness and fear[273], and positive and negative emotions[518] for autistic than non-autistic individuals may be underpinned by co-occurring alexithymia. Here, I also found that, for non-autistic individuals, alexithymia was associated with less precise, or more variable, spoken facial expressions. This could be due to the fact that those high in alexithymia have proprioceptive differences[520-522] which may lead to poorer control of their facial movements, and hence greater variability. As discussed in Chapter 7, another possibility is that alexithymic individuals are less able to draw on their own emotion concepts or emotional experiences when attempting to pose the expressions, thus resulting in more variable productions. This is plausible since previous work has found that individuals high in alexithymia typically have difficulties retrieving emotional information and memories (e.g., see

[539]). Further research is necessary to determine why alexithymia is associated with more variable expressions.

8.5. Recognition of emotion in autism

Prior to this project, studies assessing the contribution of both autistic and alexithymic traits to emotion recognition had solely relied on static snapshots of faces[209,123], omitted a non-autistic comparison group[212], and/or exclusively included female participants[212]. Therefore, it was unclear whether autistic versus non-autistic group differences in emotion recognition for dynamic stimuli, for both males and females, remain after controlling for alexithymia. To mitigate these limitations, in Chapter 2 I assessed whether there were differences in the ability to recognise emotions from dynamic stimuli for male and female autistic and non-autistic individuals matched on alexithymia. Contrary to the alexithymia hypothesis[207], the autistic participants displayed reduced recognition of angry, but not happy or sad, facial motion (at the normal 100% spatial and speed level), relative to alexithymia-matched non-autistic participants. Furthermore, I found that the level of autistic, but not alexithymic, traits was a significant (negative) predictor of emotion recognition accuracy for angry facial motion. As such, our findings contradict the alexithymia hypothesis[207], by demonstrating that difficulties recognising anger from facial motion specifically pertain to autism, and not alexithymia. These findings contribute to a growing literature suggesting that autistic individuals have particular difficulties recognising angry expressions (e.g., [147,191,219-223]). Notably, however, the majority of these previous studies did not measure alexithymia (e.g., [219-223]) and in those that did, autistic and alexithymic traits were highly correlated[147], making it difficult to determine whether differences in anger recognition were attributable to autism or alexithymia. Our study resolves this ambiguity and highlights that difficulties with recognising angry expressions at the 'normal' spatial and speed level may be related to autism, not alexithymia.

Although I found moderate evidence that autistic individuals have difficulties recognising anger in Chapter 2 (N = 60), it is important to note that I did not replicate this finding in Chapter 5 (N = 90). There are a number of potential explanations for this discrepancy. One explanation is that were differences in the characteristics of the samples investigated in Chapters 2 and 5, which led to the discrepant findings. Since I found emotion recognition difficulties in a younger (mean age = 30.14), and not older (mean age = 35.51), sample of autistic adults, it could be that the older participants had developed effective compensatory mechanisms to allow them to achieve comparable accuracy (see section 8.6.1). Although this is a possibility, meta-analytic evidence suggests that differences between autistic and non-autistic individuals in emotion recognition become larger with age (see [191]), thus contradicting this explanation. Alternatively, the discrepant findings could be due to variation in the proportion of males and females in each of the samples. Whilst I found differences in the ability to recognise anger when approximately 45% of the sample were female, I did not find such differences when 67% were female. Therefore, it is possible that female autistic individuals have less difficulty recognising facial expressions than their male counterparts, which resulted in comparable emotion recognition when this group were the majority (Chapter 5). This is particularly plausible as previous studies have demonstrated that autistic women tend to have better emotion recognition than their male peers (e.g., [544]). Further research is necessary to characterise what subgroups of autistic individuals have difficulties with emotion recognition, and for which tasks, and for which emotions.

If it is true that autistic individuals have greater difficulties recognising anger than happiness or sadness, as found in Chapter 2 and in numerous empirical studies (e.g., [147,191,219-

[223]), an important question concerns why. Our results suggest that such difficulties are not underpinned by challenges recognising high-speed expressions (see Chapter 2), or due to group differences in the core speed representation (Chapter 3), the precision or differentiation of visual representations (Chapter 5) or emotional experiences (Chapter 6), or the understanding or differentiation of semantic emotion concepts (Chapter 6). As such, our results force us to consider alternative explanations for why autistic individuals may have specific difficulties recognising angry facial expressions.

As suggested in Chapters 2 and 7, one possible explanation concerns facial information sampling. Previous work has demonstrated that autistic individuals typically attend more to the mouth, and less to the eye region, than their non-autistic peers when recognising emotional expressions (e.g., [224-226]; though also see [359]). This could be due to a number of factors. For example, it could be that autistic individuals adopt this strategy to modulate the activity of their amygdala – which may be atypical in response to faces[229,390-399] – since the amygdala is highly responsive to the eye region of emotional expressions[400]. As highlighted in Chapter 7, another potential explanation is that, since autistic individuals rely more on the mouth, and less on the eyebrows to signal anger themselves, they are more likely to attend to this area more. In either case, such attentional biases could result in difficulties recognising angry faces because the majority of the expressive information is thought to be displayed in the upper part of the face[227,228]. This may not be the case for happiness and sadness because, for these emotions, the mouth contains relatively more expressive information[379,401]. Future research should aim to formally test whether differences in facial information sampling underpin any emotion-specific recognition difficulties in autism, and determine whether differences in the *production* of emotional facial expressions contribute to differences in the *sampling* and *recognition* of them.

8.6. Links between the conceptualisation, experience, visual representation, production and recognition of emotion

Throughout this project, I discovered links between the conceptualisation, experience, visual representation, production and recognition of emotion (for non-autistic individuals; see section 8.6.1 for a description of links for autistic individuals). When considering these links, it is useful to consider theoretically *how* they could arise developmentally. Such developmental perspectives provide suggestions about how these links form, are maintained and updated. According to constructionist theories, an emotion concept like happiness evolves as sensory, affective, and motor information (amongst other information) is integrated across numerous instances where happiness is perceived in oneself or others[13,43]. From a developmental standpoint, when a caregiver labels a child's emotion as "happiness", the child will bind together sensory information from their environment (e.g., the sight of one's beloved teddy bear), neurophysiological information about their own core affective state (e.g., positive valence, medium-high arousal), motor responses (e.g., a smiling facial expression), and so on, with this emotion label, to form an instance of happiness[13]. Similarly, when a caregiver describes themselves as feeling "happy", the child will integrate sensory cues from the environment – including information concerning their caregivers' facial expression, body language, tone of voice, and so on – into their concept for happiness[13]. Across these instances, the multimodal information is integrated, and thus the conceptual knowledge about happiness accumulates[13]. Hence, over time, the experience (i.e., core affect), visual representation (i.e., sensory information), production (i.e., motor responses), and recognition of emotion all become linked, bound together by emotion labels.

According to constructionist theories, after a child forms such concepts, they can combine the corresponding information in diverse and flexible ways to help them make predictions about their own and others' emotions[13]. Over time these predictions are thought to become increasingly precise: the accumulation of conceptual knowledge allows children to move away from experiencing and perceiving emotions as "good" and "bad" (i.e., based on valence), towards experiencing and perceiving them more precisely – based on arousal, context, motor responses, and so on[50]. Following this idea, I reasoned that individuals with more precise and differentiated information within their emotion concepts – in terms of the semantic meanings, affective states, visual representations (i.e., sensory information), and facial expressions (i.e., motor responses) associated with distinct emotions – would have a more precise and differentiated framework for categorizing their own and others' emotions. Our logic was that if, for example, your concepts for anger and sadness are overlapping – perhaps they are associated with similar core affect, visual representations, motor responses (e.g., facial expression), or have a similar semantic meaning to you – it will be difficult to distinguish whether you and others are feeling angry or sad. If, on the other hand, your concepts are differentiated for highly similar emotions, such as irritation and frustration, you are likely to be able to categorise yours and others' emotions precisely as such. In the current project, I found some evidence to support this idea for non-autistic participants in Chapters 4, 5, 6, and 7 (see section 8.6.1 for a visual representation of these relationships). This evidence will be discussed, along with potential theoretical explanations for these links, below.

Although contemporary theories suggest that emotion concepts play a vital role in shaping how individuals "construct" both emotional experiences and emotion perceptions[13,50-55], prior to this project, there were no clear predictions about the mechanistic pathway by which this may occur. As mentioned in Chapter 6, there are a few logical possibilities: (1) semantic emotion concepts could impact upon emotional experiences and emotion perceptions directly and independently, (2) semantic emotion concepts could influence emotion perceptions and then in turn emotional experiences, or (3) semantic emotion concepts could influence emotional experiences and then in turn emotion perceptions. In Chapter 6, through systematic comparison of mediation models, I demonstrated that the latter is the most mathematically plausible – having more differentiated semantic emotion concepts *may* lead to individuals having more differentiated emotional experiences, and then in turn to greater emotion recognition accuracy (see Figure 8.1 left). This work provides a unique theoretical contribution to the literature by identifying a potential mechanistic pathway between the conceptualisation, experience, and perception of emotion. Nevertheless, future research employing causal manipulation and/or longitudinal methods should be conducted to test this hypothesis formally (see section 8.7 for a full discussion).

Following on from these findings, an important question concerns how theoretically these variables are linked. That is, why is it that an individual with more differentiated semantic emotion concepts also tends to have more differentiated emotional experiences, and why an individual with more differentiated emotional experiences tends to have better emotion recognition. With respect to the former, it is conceivable that having precise and differentiated definitions allows individuals to draw boundaries between the meaning of different emotions, and thus distinguish how they are feeling. For example, some individuals may use labels like "frustration" and "irritation" interchangeably to describe "*a form of annoyance*" whereas others may make more precise distinctions. These latter individuals may conceptualise frustration as "*annoyance that arises when an individual is prevented from achieving their goal or fulfilling a need*" and irritation as "*annoyance that arises in response to a repetitive unpleasant event*", thus defining the boundary between these highly similar emotions – here, based on context. While the former individual may struggle to distinguish whether they are feeling "frustrated" or "irritated" when they experience the relevant affective state, the latter individual will be able to identify that they are feeling "frustrated" rather than "irritated" because their emotion occurred in response to being prevented from achieving their goal (for example). Hence, understanding the *meaning* associated with an emotion may help an individual to categorise and differentiate their own experiences of those emotions.

The latter relationship, that those with more differentiated emotional experiences tend to have a better ability to read others' emotions, is perhaps more difficult to explain. One potential explanation concerns motoric simulation (see [545]). It is well-documented that neurotypical individuals spontaneously simulate other people's facial expressions (i.e., recreate the motor production to some extent)[546-552]. Notably, contemporary theories propose that such simulation (i.e., subthreshold motor activity) triggers partial, often unconscious, activation of other neural systems implicated in *experiencing* the relevant emotional state, which helps the perceiver to implicitly infer the emotion of the expresser (see [545]). Supporting this idea, a substantial body of evidence suggests that producing emotional facial expressions modulates one's experience of emotion (e.g., [553-558]; though see [559]), and that motoric simulation leads to enhanced facial emotion recognition[560-564]. Compelling evidence for the latter comes from studies demonstrating that targeted disruption of specific facial muscles selectively impairs the recognition of expressions that involve such muscles[563,564]. Together, this evidence raises the possibility that when an individual encounters an emotional expression, they simulate it, leading to partial induction of an emotional state, which then helps them to infer the emotion of the interaction partner (see [545] for a full discussion). So how could these findings explain the relationship between emotion differentiation and emotion recognition specifically (as found in Chapters 4 and 6)?

One idea is that, if an individual has overlapping emotional experiences, after simulating an incoming facial expression, it will be difficult for them to determine whether the partially activated affective state is one emotion or another, thus leading to downstream difficulties recognising the displayed emotion. For example, consider an individual who perceives and then simulates an expression with a downturned mouth, which induces a negatively valenced affective state with medium-high levels of arousal. If this individual has poorly differentiated experiences of anger and sadness, the affective state induced by the motoric simulation could be perceived as either one of these emotions, which could lead to this individual incorrectly categorising the expresser's emotion. Conversely, if an individual has well-differentiated experiences of these emotions, they will be able to determine that the state induced by the motoric simulation is anger, for example (assuming that they express anger in the same way as the expressor). Notably, under this simulation account, the reverse direction of causality is also possible. That is, this model can explain why having a superior ability to *recognise* emotional facial expressions may lead to a better ability to *differentiate* one's own emotions. To illustrate this idea, consider an individual who produces an expression with a downturned mouth, which is then accurately mimicked by an observer. If this individual has superior emotion recognition, they will be able to identify that the emotion mimicked by the observer corresponds to sadness, thus allowing them to indirectly infer that they themselves are feeling sad (providing this individual assumes that they are experiencing the same emotion as the interaction partner). In contrast, an individual with poorer emotion recognition may struggle to recognise the mimicked emotion, and thus incorrectly categorise their own emotions. These explanations are compatible with our results suggesting a bidirectional relationship between emotion differentiation and emotion recognition (see Chapter 4). Nevertheless, although such explanations are plausible, further work is needed to test whether motoric simulation underpins the link between the differentiation and recognition of emotion, and to determine the degree of causality and directionality between these variables.

Relatedly, our finding that the precision of one's own facial expressions contributes to the recognition of others' expressions (as found in Chapter 7) can also be explained under the simulation account. In Chapter 7, I found that non-autistic individuals high in alexithymia tended to produce less precise (i.e., more variable) emotional facial expressions, and had co-occurring difficulties recognising other people's emotions. Taking influence from simulation accounts, it is plausible that highly alexithymic individuals are less able to precisely simulate the facial expression of the interaction partner (perhaps due to poorer proprioceptive awareness; see [520-522]), and thus are less likely to trigger the congruent emotional state, leading to incorrect categorization of the interaction partner's emotion. At present, this is merely speculation. Further work is necessary to test whether alexithymia is associated with poorer facial motor control, and whether difficulties simulating facial expressions contribute to the emotion recognition challenges often seen for highly alexithymic individuals.

Prior to conducting this project, based on template matching and signal detection models, I theorised that the precision and differentiation of visual representations could contribute to emotion recognition. As discussed in Chapter 1, according to template matching models, incoming facial expressions are compared to stored "templates" of anger, happiness and sadness (and so on), which are each represented as the average of all previous encounters (e.g., the average angry expression, the average happy expression, etc.)[108-111]. Under these models, when an individual perceives that an incoming expression is perceptually similar to, and thus close to a template in face-space, the expression will be categorised as the corresponding emotion[108-111]. Taking influence from signal detection theory[140], I identified two features of these "templates" that could potentially influence emotion recognition: precision and differentiation. As discussed, this theory proposes that signal and noise distributions that are precise (i.e., narrow) and distinct (i.e., not overlapping) provide high sensitivity to distinguish the signal from the noise. Applying this principle, I reasoned that an individual with a precise template for anger, that is distinct from the template for sadness, should be adept at discriminating whether encountered facial expressions are closer to their angry or their sad templates, thus facilitating accurate emotion recognition. Conversely, an individual with imprecise and overlapping templates for these emotions should struggle to determine whether the incoming expression matches their angry or sad template, thus leading to emotion recognition difficulties. In this project, I found partial support for this idea: the *precision*, but not *differentiation*, of one's visual representations contributed to emotion recognition (for non-autistic individuals; Chapters 4 and 5). These results provide a significant theoretical contribution to the literature by elucidating, for the first time, that possessing precise visual emotion representations contributes to enhanced emotion recognition performance.

One may question why I did not find a significant contribution of the differentiation of visual representations to emotion recognition. As discussed in Chapters 4 and 7, it may be that the angry, happy and sad expressions that I examined here are perceptually dissimilar, and thus instances of overlap between the signal and noise distributions are relatively uncommon, leading to no effect of differentiation. Independent of this, the precision of visual representations could conceivably contribute to emotion recognition. It could be, for example, that the precision of visual representations comprises a proxy for the clarity of one's representations, which could influence emotion recognition irrespective of perceptual overlap. Moreover, as discussed in Chapter 4, the expectation literature would predict that more precise representations of upcoming stimuli would lead to enhanced emotion recognition accuracy, as higher precision signals increase prediction accuracy (see [434-437]). As such, the precision of visual representation could contribute to emotion recognition independent of the differentiation of such representations. Further research should include other emotions, which may introduce more instances of overlap, in order to assess whether an effect of differentiation emerges.

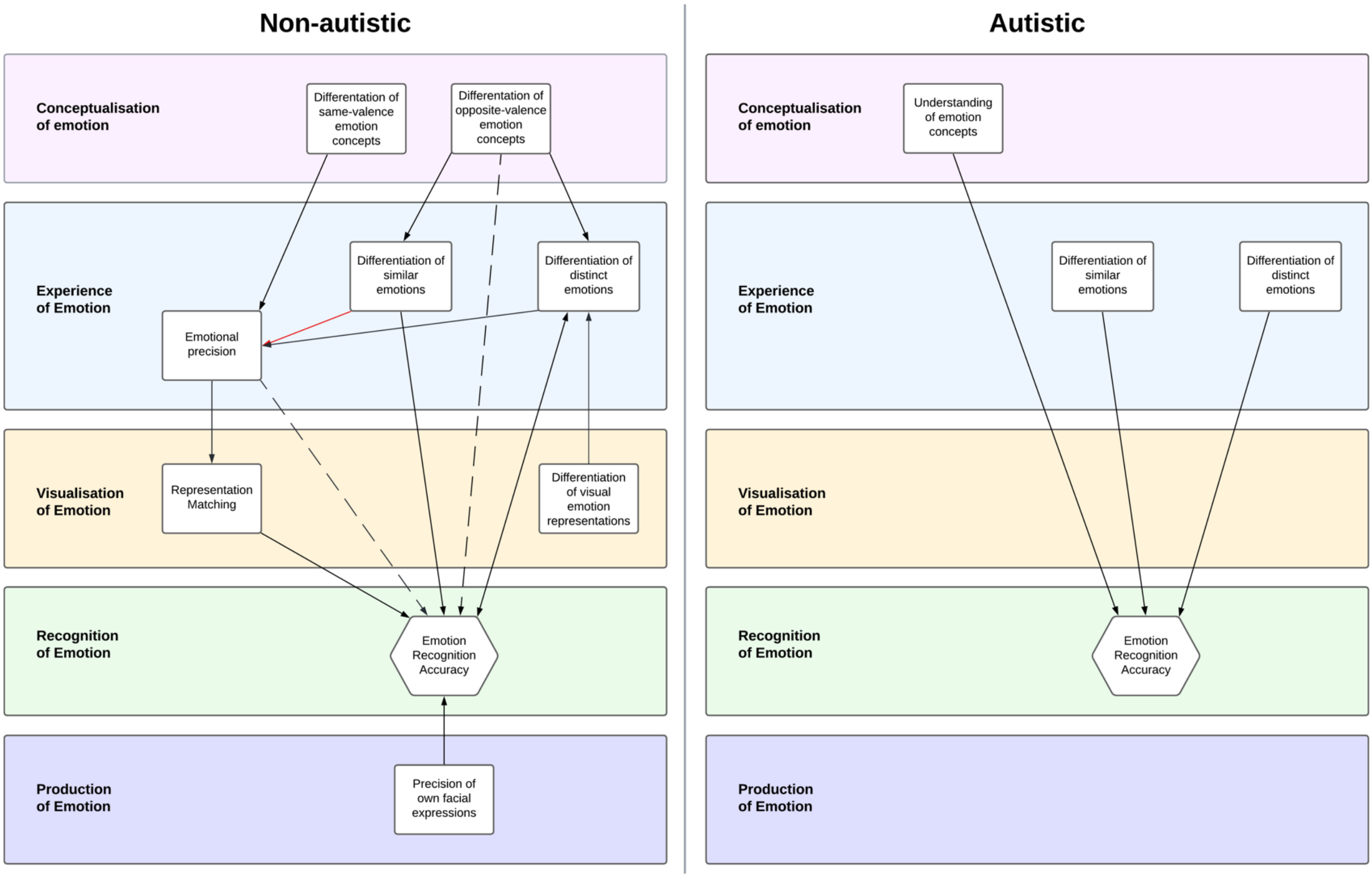
Due to the nature of how our studies unfolded, I have not yet tested whether there are links between particular emotion-related factors. For example, it is unknown whether there are links between the production of emotion, and the conceptualisation, experience, and visualisation of emotion, respectively. Determining the existence, strength, and direction of the relationships between these variables will facilitate the creation of comprehensive theoretical models linking these different emotional processes. Such work could elucidate chains of causality amongst the variables; one could ask whether having precise emotional experiences contributes to precise visual representations, and then in turn precise productions, thus leading to greater emotion recognition accuracy (for example). Future work could also benefit from applying network theory techniques to identify the most connected nodes (i.e., abilities) in the network, thus identifying the fundamental building blocks for successful emotion-processing. Such well-connected nodes could then be targeted for interventions, potentially leading to broad benefits across the whole emotion network. These interventions would also have great utility for determining directionality and causality within the network, and therefore such work comprises an important future direction for research.

8.6.1. Mechanisms involved in autistic and non-autistic emotion recognition

In the current project, I discovered that there are similarities and differences in the mechanisms involved in autistic and non-autistic emotion recognition. Specifically, I found that for both groups, the ability to differentiate one's own emotions facilitates the recognition of others' emotions (Chapters 4 and 6). However, whilst having a comprehensive understanding of emotion concepts facilitated emotion recognition for autistic people, the differentiation of such concepts was important for non-autistic emotion recognition (Chapter 6). Here I also found that, for non-autistic people, the ability to precisely visualise and match expressions, contributed to enhanced emotion recognition (Chapters 4 and 5). Specifically, across three distinct samples, I found robust evidence for a representational precision x matching interaction (see Chapters 4 and 5); the precision of visual representations contributed to emotion recognition for participants with a poorer ability to visually match two expressions (and not those with intact matching). Finally, for non-autistic individuals, the ability to precisely produce facial expressions also contributed to enhanced emotion recognition accuracy (Chapter 7). By contrast, the precision of visual representations and productions, and matching ability, did not predict autistic emotion recognition (see Figure 8.1). As can be seen in Figure 8.1, I identified considerably fewer abilities that contributed to autistic, than non-autistic, emotion recognition.

Figure 8.1.

A diagram illustrating the relationships I identified between the conceptualisation, experience, visualisation, production and recognition of emotion for the autistic (right) and non-autistic (left) participants.



Note. Positive relationships are shown by black lines. Negative relationships are shown by red lines. Full lines correspond to direct effects. Dashed lines correspond to indirect effects. Arrowheads illustrate hypothesised path directions.

Although there could be fewer contributing factors for autistic individuals due to additional noise, stemming from greater heterogeneity with respect to attention, perception, and general cognitive functioning (e.g., [153-155]), our Bayesian analyses provided moderate-strong evidence for these null effects (i.e., that the representational precision x matching interaction and the precision of spoken productions do not contribute to emotion recognition). As such, it seems unlikely that there are fewer contributing factors for autistic individuals due to methodological and/or statistical artefacts, but rather that there are true mechanistic differences in emotion recognition between these groups. Therefore, it is important to consider potential explanations for these findings.

The fact that fewer abilities predicted emotion recognition for autistic individuals (relative to non-autistic individuals) aligns well with Bayesian accounts of autism. Such accounts propose that autistic individuals are less affected by their prior experiences than neurotypicals, and instead place greater weight on incoming sensory information (e.g., [259-261]). In the current project, our results suggest that autistic individuals place less emphasis on stored visual (Chapter 5) and motoric (Chapter 7) representations of facial expressions (i.e., priors), than their non-autistic peers, thus supporting Bayesian theories. However, in conflict with these accounts, I found that the autistic participants were just as affected by the spatial and kinematic manipulations to facial expressions as their non-autistic peers (Chapters 2 and 5), suggesting that these individuals are not necessarily more influenced by incoming sensory information (as such manipulations influenced the sensory properties of the stimuli). Further research is necessary to determine the extent to which autistic individuals are influenced by their prior experiences, versus incoming sensory information, when interpreting others' emotions. To more sensitively assess the extent to which autistic and non-autistic participants are influenced by the sensory properties of stimuli, such future work could employ tasks with more levels of spatial and kinematic manipulation than used here (i.e., 3 spatial levels, 3 kinematic levels).

Since our results suggest that autistic individuals may be less guided by their visual and motoric representations (Chapters 5 and 7), an important question concerns *how* these individuals are able to recognise the emotion of others. As discussed in Chapters 1, 5, 6 and 7, converging evidence suggests that autistic individuals may adopt alternative compensatory strategies to facilitate emotion recognition. Previous researchers have proposed that, rather than comparing incoming expressions to their visual representations (as is likely to be the case for non-autistic individuals[108-111]), autistic people may follow a cognitively mediated "rule-based strategy", wherein they assess the degree to which the expression matches a list of features they have learnt to be associated with distinct emotions (e.g., for anger, this could be "furrowed brow)[256,257]. If this is true, one might expect emotion recognition performance to be more strongly related to cognitive ability for autistic individuals, and to visuo-spatial abilities for non-autistic individuals. Supporting this idea, here I found that IQ (Chapter 7; see also [215,258]) and the ability to understand semantic emotion concepts (Chapter 6) contributed to emotion recognition accuracy for autistic individuals, whereas non-verbal reasoning ability contributed for their non-autistic peers (Chapters 2, 4, 5 and 6). Moreover, if autistic individuals employ more effortful cognitive mechanisms, one might expect longer emotion recognition response latencies, which has repeatedly been found in the literature[229-238] (though note that there could be other explanations for this finding). Finally, if autistic individuals are following a rule-based, rather than template-matching, strategy, one may expect these individuals to have a higher tolerance for exaggeration of facial expressions (see [256,257]). The logic follows that unnaturally exaggerated expressions will appear less realistic to those employing a template-matching strategy, as these expressions will not match their templates, than those adopting a rule-based strategy, as the rules such as "furrowed brow" and "downturned mouth" are still met. Notably, previous studies have found that autistic adults select a higher proportion of exaggerated faces as realistic (than non-autistic adults), thus raising the possibility of a more rule-based strategy[256,257]. As discussed in Chapter 1, these findings do not necessarily rule out template-matching as the autistic participants could just have more exaggerated templates than their non-autistic peers (thus leading to higher tolerance for exaggeration). Nevertheless, here

I did not find evidence to suggest that autistic individuals have more caricatured visual representations in terms of speed (for point-light displays), nor consistently more exaggerated motoric representations in the spatial and kinematic domains. As such, our results point to the former possibility that autistic individuals may adopt alternative compensatory mechanisms, such as a rule-based strategy, to recognise the emotions of others. Nevertheless, future studies should aim to test this explicitly.

Relatedly, here I identified that different constellations of traits were involved in autistic and non-autistic emotion recognition. Specifically, for non-autistic individuals, I identified that those with superior non-verbal reasoning ability (Chapters 2, 4, 5, and 6) enhanced communication (as indexed by low scores on the AQ Communication subscale; Chapter 6, though see Chapter 5), and lower levels of alexithymia (Chapter 7; though note that this effect was marginally significant) displayed elevated emotion recognition accuracy. By contrast, for autistic individuals, those with higher IQ (Chapter 7), better understanding of semantic emotion concepts (Chapter 6) and (surprisingly) greater difficulties identifying feelings (Chapter 6) were typically more accurate at recognising emotional expressions. As discussed in Chapter 6, one potential explanation for this latter, unexpected, finding is that participants who had greater difficulties identifying their feelings tried harder on the emotion recognition task to compensate for their difficulties, resulting in elevated performance. This effect may be larger in the autistic group because these individuals are more likely than their non-autistic counterparts to underestimate their emotional abilities[292]. Further research is necessary to test whether effort mediates the relationship between difficulties identifying feelings and emotion recognition for autistic individuals, and to elucidate other traits contributing to autistic and non-autistic emotion recognition.

8.7. Implications, strengths, limitations and future directions

In the following section, I discuss the implications of our findings, outline general strengths and limitations of our studies (see specific limitations for each study in each empirical chapter), and highlight important future directions for research.

There are a number of important implications of our findings. Firstly, the results of this project illuminate pathways to supportive interventions to help *both* autistic and non-autistic people to accurately recognise emotional facial expressions. As mentioned previously, here I have identified similarities and differences in the factors involved in emotion recognition between groups: for autistic individuals, understanding semantic emotion concepts and being able to differentiate one's own emotions contributes to enhanced emotion recognition; for non-autistic individuals, being able to differentiate semantic concepts and experiences of emotions and precisely visualise and match emotional facial expressions predicts superior emotion recognition performance. These abilities comprise useful candidate mechanisms that, if trained, may improve emotion recognition within each group.

For both groups, training individuals to be able to differentiate their own emotions could lead to improvements in the recognition of others' emotions. Such interventions could elicit broad benefits - enhanced emotion differentiation is not only associated with superior emotion recognition but also with adaptive emotion regulation, improved psychosocial functioning, and decreased mental health difficulties (see [293,440,501-505] for reviews). This is particularly pertinent here as mental health issues are highly prevalent in the autistic population[565-574], with as many as 71% of autistic individuals meeting criteria for at least one mental health disorder[565]. Alternatively, one could aim to improve conceptual understanding of emotions for autistic people, and improve the differentiation of these concepts for non-autistic people, thus leading to enhanced emotion recognition. In line with this, recent work employed a five-day intervention which aimed to increased conceptual emotion knowledge by giving detailed information about each emotion concept and then by comparing the emotion concepts to one another (thus targeting both general understanding of emotions and the differentiation of emotion concepts)[506]. This intervention successfully improved conceptual emotion knowledge and downstream emotion differentiation performance, relative to an active control group, which remained at follow-up a month later[506]. Our results suggest that this intervention may also have a positive impact on emotion recognition accuracy for both autistic and non-autistic people, though this should be tested in future investigations.

Beyond these implications, here I make a significant methodological contribution to the literature by introducing a variety of novel paradigms, each with their own advantages, for assessing the conceptualisation, experience, visualisation, and production of emotion, and making these openly accessible to the broader scientific community. Firstly, our EmoMap paradigm facilitates the assessment of emotion differentiation without requiring participants to translate their emotional experiences into words. By contrast, existing methods (e.g., momentary time sampling and photo emotion differentiation tasks) rely on participants labelling their emotions or rating the extent to which they experience different emotions on several scales. Although language plays a constitutive role in the experience of emotion (see [55]), the tasks we use to assess it (e.g., emotion differentiation) should not require labelling of emotional state for several reasons. Firstly, the differentiation of emotional states is not necessarily dependent on labelling those states. For example, someone might struggle to label their butterfly sensation as 'excitement', but still be able to identify that the feeling is not the same as contentment or nervousness. Second, individual differences on existing tasks may simply be the product of differences in language ability (e.g., ease or difficulty accessing appropriate emotion labels). That is, on these tasks, someone may score poorly on 'emotion differentiation' simply because they struggle to translate their emotional experiences into words, rather than due to any difficulties differentiating emotional signals. This is plausible since verbal IQ is associated with emotion differentiation on such language-dependent tasks[295]. Finally, existing tasks may not be appropriate for assessing emotion differentiation across development (see [438]), clinical groups with varying language ability (e.g., autistic people, people with aphasia, dementia, etc.[151,495,496]), or across languages, where there are often no direct translations of emotion labels. By asking participants to respond based on the similarity of their emotional experiences, our EmoMap paradigm mitigates these limitations, and thus could have great utility across numerous populations (see [450] for full discussion).

Secondly, to our knowledge, our ExpressionMap paradigm is the first task specifically designed to index the precision and differentiation of visual emotion representations. By contrast, previous studies have typically adopted psychophysical approaches (e.g., [384,388,389,463-465]), which facilitate the construction of comprehensive visual emotion representations that can vary across numerous spatiotemporal dimensions (e.g., onset latency, offset latency, acceleration, peak amplitude). Whilst these methods allow researchers to quantify many aspects of participants' imagined representations, these methods typically require thousands of trials, and thus can take many hours to complete (usually over 6 hours if studying all six basic emotions). So far, such methods have overlooked accompanying features of these representations, for example precision and differentiation. Nevertheless, assessing these features should be a priority because the precision and differentiation of visual emotion representations may vary across emotions, cultures and participant groups (as is the case with the appearance of these representations[384,388,389,464,464,472]), and play a key role in emotion recognition (Chapters 4 and 5). Here, I have introduced a method that facilitates the assessment of these important constructs in just 20-30 minutes (see [468] for full discussion).

Finally, to the best of our knowledge, our FaceMap paradigm is the first to assess the spatiotemporal and kinematic properties of emotional expressions, after minimising the influence of facial morphology across participants (using facial motion retargeting). As such, our task is appropriate for analysing expressions across ages, genders, ethnicities and clinical groups, which may all differ in morphology[279-282,575-577]. In addition, by allowing researchers to retarget emotional expressions on to photorealistic avatars, this paradigm facilitates the production of stimulus videos which can be used in future experiments (with participants' consent). Here, there is the opportunity to retarget the same facial movements onto different identities, which vary in age, gender, ethnicity, or spatial configuration (e.g., larger eyebrows, more angular eyebrows), to assess the influence of these factors on the social (e.g., trustworthy, dominant, kind, etc.) and emotional judgments we make about others, whilst controlling for differences in facial movements. For example, researchers could retarget the same angry expression on to avatars that differ in race (e.g., Asian, Black, Latinx, White, etc.), and then ask participants to make a social judgement about the expresser (e.g., how aggressive the expresser appeared), thus assessing the contribution of race to social judgements in a highly controlled manner. In sum, this paradigm and the associated stimuli have great utility for numerous scientific fields (e.g., social psychology, affective science, clinical psychology).

Another methodological strength of this project concerns the inclusion of dynamic, rather than static, emotional facial expressions. Although facial expressions are inherently dynamic in nature, the vast majority of studies in the literature have employed static stimuli in their experiments (79-100% of studies in meta-analyses; see [191,217]), and thus dynamic features of expressions such as speed or temporal order have been overlooked. To remedy this limitation, here I examined visual emotion representations and emotion recognition using dynamic stimuli, and specifically assessed the contribution of speed cues to these factors.

Relatedly, in the current project, I employed point-light displays, which provide a way of studying core dynamic cues (e.g., speed), while controlling other perceptual dimensions[445,446], such as identity (e.g., gender, age, ethnicity, face attractiveness), depth and pigmentation, which are all known to influence emotion recognition[376,377,447]. Hence in this project, by using dynamic point light displays, I was able to accurately assess the contribution of kinematic cues to visual emotion representations and emotion recognition, without these other cues confounding the results. Whilst using point-light displays facilitates highly controlled assessment of visual-processing, it is important to note that these stimuli have low ecological validity, and thus our findings may not generalise to full emotional expressions. For example, it could be that the expressions that autistic and non-autistic people picture in their "mind's eye" differ on other dimensions not tested here, such as spatial configuration or level of spatial exaggeration (but not differ in speed). This is plausible since previous research suggests that autistic individuals require static angry expressions to be higher in intensity for them to be correctly identified[222], suggesting that these individuals may have more exaggerated visual representations of anger in the spatial domain. Since I found that autistic individuals display lower activation of numerous eye, eyebrow, cheek and mouth blendshapes (see Chapter 7) when expressing happiness, it could be that there are also differences between groups in visual representations for happy expressions in the spatial domain (assuming that there are links between our own productions and what we see in the mind's eye). Alternatively, it may be that the emotion recognition differences documented here (lower recognition of anger for autistic individuals; see Chapter 2) may not be present for full emotional expressions, due to other perceptual cues facilitating autistic emotion recognition. Whilst this is a possibility, there are numerous studies suggesting that autistic individuals have difficulties with full static and dynamic angry expressions (e.g., [147,191,219-222]), and thus our results are representative of the broader literature. Finally, it may be that the links I have demonstrated between the experience, representation and recognition of emotion exist for point-light displays (see Chapter 4), but not full emotional expressions. Although this is possible, since individuals are thought to compare incoming facial expressions to stored visual representations, which comprise the average expressions they have encountered previously[108-111], it seems unlikely that the precision of such representations would only be important for recognising emotion in PLFs (which are not typically encountered). Similarly, there is no clear reason why an individual would draw on their own emotional experiences to recognise emotion specifically in PLFs. Rather, it seems more plausible that one's experiences and representations facilitate the recognition of 'real life' expressions (i.e., full emotional expressions), which has a downstream effect on the ability to recognise abstracted versions (e.g., point-light displays). Nevertheless, future studies are necessary to confirm whether our results generalise to full emotional expressions. Such studies could make use of the avatar stimuli that I have generated as part of this project to control for identity-effects when assessing visual emotion representations and emotion recognition.

Another limitation of this project is that I specifically focused on just three emotions: anger, happiness, and sadness. As previously discussed, I did not include all six of the basic emotions (i.e., include also fear, disgust and surprise) because this would have doubled the length of each of the tasks, thus compromising our ability to reach our desired sample sizes (due to limits on resources). Our decision to focus on anger, happiness and sadness, specifically, was motivated by a number of factors. Firstly, I selected these emotions as they occupy different regions within the circumplex model of affect[41] – varying in both arousal and valence – and in face-space (e.g., [381,578,579]) – varying across numerous spatiotemporal and kinematic dimensions (e.g., [239,384]). Second, I selected anger, happiness, and sadness as previous research has demonstrated that it is possible to selectively induce these discrete emotions with images (e.g.,

[430]), whereas it is not yet possible to do so for more complex emotions (e.g., awe, guilt, embarrassment, etc.). Third, in our first empirical chapter (Chapter 2), I specifically aimed to test whether causally manipulating the spatial and kinematic properties of angry, happy and sad expressions influenced emotion recognition for autistic individuals to the same extent as had previously been found for neurotypicals (in Sowden et al[239]). Thus, it was important to ensure that I included the same emotions as used in previous investigations. Finally, the results from the first empirical study raised a number of hypotheses specifically pertaining to anger, happiness and sadness, that I subsequently tested throughout the project (e.g., difficulties recognising anger, but not happiness or sadness, may be due to specific differences in speed representations and/or productions of anger). Thus, after this first study, my scientific line of enquiry concerned specifically these three emotions. Nevertheless, future studies should aim to replicate our findings with a broader set of emotions, perhaps starting with the six basic emotions, and then including more complex emotions, such as awe, guilt and embarrassment. As mentioned, the inclusion of other emotions may introduce greater instances of perceptual overlap, and thus other effects may emerge (e.g., differentiation of visual representations on emotion recognition).

A further limitation is that here I assessed alexithymia using the self-report Toronto Alexithymia Scale. Although 89% of studies assessing emotional self-awareness in autism employ self-report measures[149], some researchers have raised concerns about their efficacy (e.g., [365-367]), arguing that "people with alexithymia, by definition, should not be able to report their psychological state"[366]. Essentially, using self-report measures may result in noisy estimates of alexithymic traits, which do not map on to true, objectively measured, levels. However, at present, attempts to develop objective methods to index alexithymia are in their infancy (e.g., [367,368]), and thus researchers are forced to rely on self-report measures.

In the current project, our decision to use the TAS-20 was motivated by a number of factors. Firstly, I selected the TAS-20 because it is widely regarded as the gold-standard tool for assessing alexithymia (used in 62% of studies in [149]) due to its strong psychometric properties (e.g., [344,351]). Secondly, since I aimed to assess whether the alexithymia hypothesis applies, not only to emotion recognition for static but also dynamic expressions, it was important for us to employ the same measure as used previously (i.e., the TAS-20 as in [209,212,213]). Although using the TAS-20 was advantageous in the current project, it is important to acknowledge its limitations. For example, some researchers have argued that the TAS-20 taps into levels of psychological distress rather than intrinsic difficulties identifying and describing emotions (e.g., [368-372]). Other critics highlight that the TAS-20 solely assesses the "cognitive" component of alexithymia (i.e., reduced awareness and cognitive processing of emotional feelings) and not the "affective" component (i.e., reduced experiences emotional feelings e.g., reduced arousal)[374]. As such, future studies should aim to replicate our results using alternative measures of alexithymia such as the Perth Alexithymia Questionnaire[373] or the Bermond Vorst Alexithymia Questionnaire[374], which somewhat mitigate these limitations.

It is also important to highlight that I am unable to conclusively infer causality and directionality in this project due to the observational nature of the studies. In this project, I have attempted to identify the most mathematically plausible path directions between the conceptualisation, experience, visualisation, and recognition of emotion by systematically reversing the paths in our structural equation models. Whilst our data highlight path directions that are mathematically plausible (e.g., emotional precision → representation matching → emotion recognition; differentiation of concepts → differentiation of experiences → emotion recognition), future studies are necessary to confirm that these variables are causally linked, and in the specified directions. Longitudinal research that examines how the conceptualisation, experience, visualisation, production and recognition of emotion change across development will be particularly beneficial for establishing directionality. Such work could employ cross-lagged structural equation models to unpick the relationships between variables across timepoints (e.g., does the differentiation of emotion concepts at age three predict the differentiation of emotional experiences at age ten), and latent growth models to identify specific developmental trajectories in emotion-processing. Additionally, research that involves causal manipulation (e.g., semantic satiation to cause emotion concepts to temporarily lose meaning, training individuals to differentiate emotion concepts) will be useful for determining the extent of causality between these variables.

Finally, it is also important to highlight the limitations of this project with respect to sample generalisability. Although here I redressed the bias in extant autism research by specifically focusing on the abilities of autistic *adults*, and ensuring that autistic *women* were included throughout, there are a number of limitations of the samples recruited in the current project. In all of the studies discussed here, the participants were predominantly white, highly educated or intelligent, English-speaking individuals from the United Kingdom. Therefore, our results may not be representative of those with lower levels of education or with intellectual disabilities, or those from different racial, ethnic, or cultural backgrounds. With respect to the former, although I did not find any group differences in the understanding or differentiation of emotion concepts, or in the precision or differentiation of emotional experiences here, differences between groups may emerge for autistic individuals with intellectual disabilities. Similarly, whilst I found no group differences (Chapter 5) or some group differences (Chapter 2) in emotion recognition, greater differences may emerge for those with intellectual disabilities. This is particularly plausible; previous evidence suggests that whilst autistic individuals with average to high IQs often have comparable emotion recognition performance (e.g., [207,244,477,478]), those with co-occurring intellectual disabilities have difficulties with emotion recognition (e.g., [215,489,490]), relative to mental age or IQ-matched comparison groups (though see [491]). Hence, our findings may underestimate the emotion recognition difficulties faced by large proportions of the autistic community since the participants generally possessed high levels of intelligence. Further work is needed to characterise the emotion recognition performance of autistic people with co-occurring intellectual disabilities, and identify whether these difficulties are attributable to autism, intellectual disability, or the interaction between these factors.

As mentioned, the results in this thesis may not represent those from different ethnic or cultural backgrounds. In particular, it may be that those from other cultures (e.g., Eastern) have different visual representations or productions of emotion, as has been found previously (e.g., [388,389,463-465]). For example, one study identified that individuals from Western Cultures tended to emphasise the eyebrows and mouth in their representations, while those from East Asian cultures tended to emphasise expressive information in the eye region[388]. Hence, as mentioned in Chapter 7, in this project it may be that the Western participants display greater activation of the eyebrow and mouth when posing different emotional expressions, relative to what would be seen with East Asian participants. Since autistic individuals also tend to exhibit lower activation of these regions when posing specific emotional expressions (e.g., happiness; see Chapter 7), it may be that differences between autistic and non-autistic people in facial expressions are smaller in East Asian cultures. Further research is necessary to test whether this is the case.

8.8. Conclusion

This project examined whether there were differences between autistic and non-autistic adults in the conceptualisation, experience, visual representation, and production of emotion after controlling for alexithymia, and determined whether these abilities contributed to emotion recognition for autistic and non-autistic people. Taking influence from constructionist, template-matching, and signal detection accounts, I created mathematically plausible, mechanistic models elucidating the processes involved in autistic and non-autistic emotion recognition, and outlined how, theoretically, these links could form. Specifically, I first found evidence to suggest that alexithymia may underlie some, but not all, of the differences between autistic and non-autistic people in emotion-processing. Second, I discovered similarities and differences in the processes involved in emotion recognition for these groups. By elucidating several candidate mechanisms underpinning superior emotion recognition, the current project paves the way for future supportive interventions to help individuals to accurately interpret others' emotions, thus ultimately fostering more successful and fluid social interactions.

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Appendix 1

Supplementary Materials for Chapter 2

Differences between autistic and non-autistic adults in the recognition of anger from facial motion remain after controlling for alexithymia.

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(Published in the *Journal of Autism and Developmental Disorders*)

Reference: Keating CT, Fraser DS, Sowden S, Cook JL. Differences between autistic and non-autistic adults in the recognition of anger from facial motion remain after controlling for alexithymia. Journal of autism and developmental disorders. 2022 Apr;52(4):1855-71. https://doi.org/10.1007/s10803-021-05083-9

Appendix 1.1 – Participants' ethnicities in Chapter 2

Table A1.1.

Participant written responses to the question 'What is your ethnic group?'.

Ethnic group	N	%
White English/Welsh/Scottish/Northern Irish/British	25	41.7
White/Caucasian	8	13.3
White Polish	6	10.0
White Portuguese	2	3.3
White Italian	2	3.3
Mixed/Multiple Ethnic Groups- White and Asian	2	3.3
European	2	3.3
Polish	2	3.3
Black African	1	1.7
Mixed/Multiple Ethnic Groups- Other	1	1.7
Asian Pakistani	1	1.7
Asian Indian	1	1.7
White Slavic	1	1.7
White Albanian	1	1.7
Black Caribbean	1	1.7
White Hungarian/Greek	1	1.7
British	1	1.7
Latino/Hispanic	1	1.7
White European	1	1.7

Appendix 1.2 – Quantity of autistic participants that met criteria for an autism diagnosis

The level of autistic characteristics of 22 individuals in the ASD group was assessed using the Autism Diagnostic Observation Schedule (version 2 (ADOS-2)[345]. Of the 22 who completed the ADOS-2 assessments, 16 met ADOS criteria for ASD (7 autism, 9 autism spectrum). Although six individuals in the ASD group did not meet criteria for ASD according to the ADOS, they had previously received diagnoses from independent clinicians, and thus still participated in the study. Unfortunately, it was not feasible to complete observational assessments on all ASD participants due to restrictions on face-to-face testing during the COVID-19 pandemic.

Appendix 1.3 – Binary accuracy analysis

To facilitate completion of a binary accuracy analysis (i.e. correct; 1 or incorrect; 0), we transformed the data such that participants scored 1 when they gave the highest emotion rating to the correct emotion, and 0 when they rated either of the incorrect emotions higher than the correct emotion. We then multiplied these values by 100 such that the emotion recognition scores would reflect percentage accuracy (i.e. the percentage of trials where participants gave the highest rating to the correct emotion). We then submitted these binary accuracy scores to a 2 x 3 x 3 x 3 Analysis of Variance (ANOVA) with the between-subjects factor *group* (ASD, control) and the within-subjects factors *emotion* (happy, angry, sad), *stimulus spatial level* (S1, S2, S3), and *stimulus kinematic level* (K1, K2, K3).

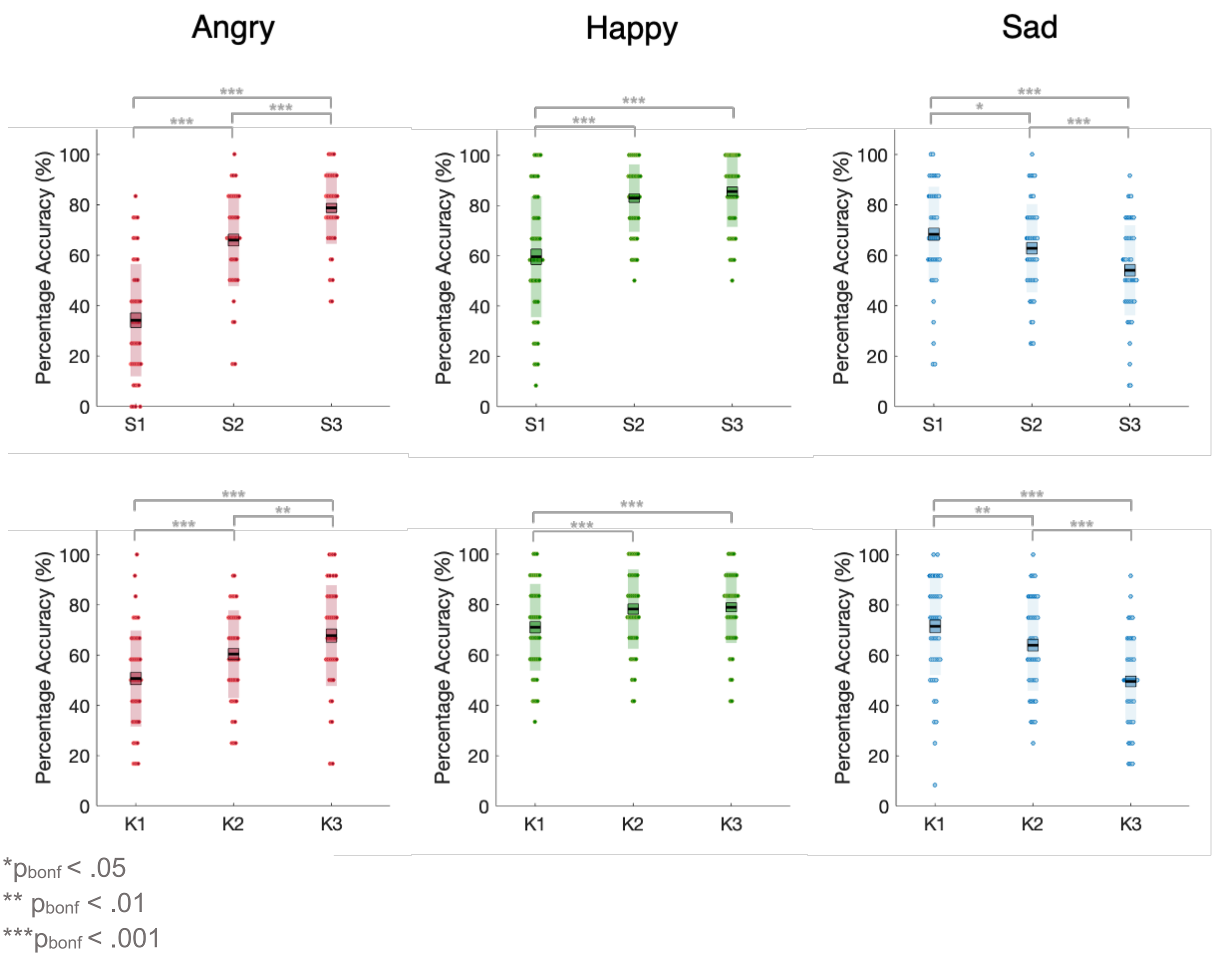
Mirroring the results reported in the main manuscript, this analysis revealed a significant main effect of emotion [$F(2, 116) = 27.05$, $p < .001$, $\eta_P^2 = .32$, $BF_{10} = 5.66e^{21}$], with percentage accuracy highest for happy [mean(SEM) = 76.10(1.73)], and comparable for angry [mean(SEM) = 59.76(1.99)] and sad [mean(SEM) = 61.74(1.89)] expressions.

We also identified a main effect of spatial level [$F(2,116) = 109.11$, $p < .001$, $\eta_P^2 = .65$, $BF_{10} = 6.01e^{29}$], with percentage accuracy lowest at the S1 level [mean(SEM) = 54.14(1.74)] and comparable at the S2 [mean(SEM) = 70.62(1.40)] and S3 [mean(SEM) = 72.84(1.26)] levels. In line with the findings reported in the main manuscript, the effect of spatial level was qualified by an emotion x spatial interaction [$F(4,232) = 80.66$, $p < .001$, $\eta_P^2 = .58$, $BF_{10} = 2.77e^{54}$]. Post-hoc repeated measures ANOVAs revealed that whilst there was an effect of the spatial manipulation for all three emotions (all $F > 18$, all $p < .001$) , the direction of the effect varied between high and low arousal emotions (mirroring the results reported in the main manuscript): percentage accuracy for angry and happy expressions were highest for 150% spatial extent (S3) [angry mean(SEM) = 78.82(1.84); happy mean(SEM) = 85.67(1.78)], followed by 100% spatial extent (S2) [angry mean(SEM) = 66.13(2.30); happy mean(SEM) = 82.97(1.74)], followed by 50% spatial extent (S1) [angry mean(SEM) = 34.32(2.84); happy mean(SEM) = 59.67(3.11)]. In contrast, accuracy improved for sad expressions as the level of the spatial manipulation decreased [S3 mean(SEM) = 54.02(2.33); S2 mean(SEM) = 62.76(2.27); S1 mean(SEM) = 68.44(2.42)]; Figure A1.1].

In addition, we identified a main effect of kinematic level [$F(2,116) = 4.651$, $p < .05$, $\eta_P^2 = .07$, $BF_{10} = 0.04$], with percentage accuracy highest at the K2 level [mean(SEM) = 67.64(1.33)], and comparable at the K3 [mean(SEM) = 65.48(1.37)] and K1 levels [mean(SEM) = 64.48(1.45)]. In line with the results reported in the main manuscript, this main effect of kinematic level was qualified by an emotion x kinematic interaction [$F(4,232) = 38.59$, $p < .001$, $\eta_P^2 = .40$, $BF_{10} = 4.80e^{18}$]. Post-hoc repeated measures ANOVAs indicated that whilst there was an effect of the kinematic manipulation across all three emotions (all $F > 11$, $p < .001$), the direction of the effect was different between high and low arousal emotions (in line with the results reported in the main manuscript): percentage accuracy for angry and happy expressions were highest for the 150% speed (K3) [angry mean(SEM) = 67.90(2.57); happy mean(SEM) = 78.90(1.84)], followed by 100% speed (K2) [angry mean(SEM) = 60.65(2.09); happy mean(SEM) = 78.30(2.01)], followed by 50% speed (K1) [angry mean(SEM) = 50.73(2.49); happy mean(SEM) = 71.11(2.17)]. In contrast, accuracy for sad expressions improved as speed decreased (K3 mean(SEM) = 49.63(2.17); K2 mean(SEM) = 63.98(2.35); K1 mean(SEM) = 71.59(2.52); Figure A1.1].

Figure A2.1.

Percentage accuracy scores, for all participants, for each emotion across the spatial and kinematic levels.



Note. The black line represents the mean, the shaded region represents the standard deviation, the coloured box represents 1 standard error around the mean and the dots are individual datapoints.

Finally, this analysis also revealed an emotion x kinematic x group interaction [F(4,232) = 2.74, $p < .05$, $\eta_P^2 = .05$, $BF_{10} = 0.13$]. In order to unpack this significant emotion x kinematic x group interaction, we conducted post-hoc 2 x 3 (group, emotion) ANOVAs for each kinematic level. This analysis revealed a significant emotion x group interaction at the K2 [F(2,116) =

3.93, $p < .05$, $\eta_P^2 = .06$, $BF_{10} = 2.89$] but not K1 [$p = .616$, $BF_{10} = 1.64e^{-4}$] or K3 [$p = .548$, $BF_{10} = 0.18$] levels. Bonferroni-correct post-hoc independent sample t-tests revealed that control, relative to autistic, participants had higher accuracy for angry videos at the 100% speed level (averaged across all spatial levels) [$t(58) = 3.30$, $p_{bonf} < .01$, mean difference = 13.77, $BF_{10} = 20.06$]. There were no significant group differences in percentage accuracy for happy [$p = .133$, $BF_{10} = 0.30$] or sad [$p = .572$, $BF_{10} = 0.68$] expressions at this 100% speed level (Figure A1.2).

Figure A1.2.

Percentage accuracy at the K2 (100%) speed level, as a function of emotion. Control in lilac, ASD in green.

**$p_{bonf} < .01$

Note. The black line represents the mean, the coloured box represents the standard error of the mean, the shaded region represents the standard deviation, and the dots are individual datapoints.

In order to establish whether any group differences at the S2K2 (100% spatial extent, 100% speed) level (that we found in the accuracy analyses in the main paper) were driving the group difference we identified for angry expressions at the K2 level (when averaged across spatial levels), we conducted a further three Bonferroni-corrected independent sample t-tests for angry expressions at the K2 level, at each of the spatial levels. This revealed that controls had significantly higher emotion recognition accuracy for angry expressions at the S2K2 level [$t(58) = 3.61$, $p_{bonf} < .01$, mean difference = 20.33, $BF_{10} = 40.59$], but not at the S1K2 [$p_{bonf} = .231$, $BF_{10} = 1.00$] or S3K2 [$p_{bonf} = .072$, $BF_{10} = 2.42$] levels, thus mirroring the results reported in the main manuscript. Hence, our findings suggest that the group difference in accuracy for angry expressions discovered at the K2 level (across the spatial levels) may be mainly driven by a group difference at the S2K2 level.

Appendix 1.4 – Unpacking the significant main effects of Emotion and Spatial level

In our main analysis, we conducted a mixed 2 x 3 x 3 x 3 ANOVA with the between-subjects factor *group* (ASD, control) and the within-subjects factors *emotion* (happy, angry, sad), *stimulus spatial level* (S1, S2, S3), and *stimulus kinematic level* (K1, K2, K3). This analysis revealed a significant main effect of emotion [$F(2,116) = 17.79$, $p < .001$, $\eta_P^2 = .24$, $BF_{10} = 4.83e^{13}$], with recognition scores highest for happy [mean(SEM) = 4.19(.19)], and comparable for sad [mean(SEM) = 3.14(.18)] and angry [mean(SEM) = 2.96(.18)] videos. The main analysis also revealed a main effect of spatial level [$F(2,116) = 259.57$, $p < .001$, $\eta_P^2 = .82$, $BF_{10} = 7.62e^{61}$], with recognition scores improving as the spatial level increased [S1 mean(SEM) = 2.04(.13); S2 mean(SEM) = 3.68(.16); S3 mean(SEM) = 4.56(.15)].

Appendix 1.5 – Unpacking the significant main effects and interactions in the emotion rating analysis

Main effects:

In order to compare the magnitude of the ratings between groups, we conducted a mixed 2 x 3 x 3 x 3 x 3 ANOVA with the between subjects factor *group* (ASD, control) and the within-subjects factors *emotion* (happy, angry, sad), *stimulus spatial level* (S1, S2, S3), *stimulus kinematic level* (K1, K2, K3) and rating (happy, angry, sad). This analysis revealed a significant main effect of emotion [$F(2,116) = 34.86$, $p < .001$, $\eta_P^2 = .38$], with ratings being highest for angry [mean(SEM) = 3.61(.12)], intermediate for sad [mean(SEM) = 3.48(.12)] and lowest for happy [mean(SEM) = 3.27(.11)] facial motion.

This analysis also revealed a main effect of spatial level [$F(2,116) = 50.52$, $p < .001$, $\eta_P^2 = .47$], with participants giving the highest ratings at the S3 [mean(SEM) = 3.70(.10)], followed by the S2 [mean(SEM) = 3.43(.11)], followed by the S1 level [mean(SEM) = 3.22(.13)]. The effect of spatial level was qualified by an emotion x spatial interaction [$F(4,232) = 3.48$, $p < .05$, $\eta_P^2 = .06$]. Post-hoc repeated measures ANOVAs revealed that the effect of the spatial manipulation was strongest for angry facial motion [$F(2,116) = 39.74$, $p < .001$, $\eta_P^2 = .41$] followed by sad facial motion [$F(2,116) = 35.25$, $p < .001$, $\eta_P^2 = .38$], followed by happy facial motion [$F(2,116) = 15.75$, $p < .001$, $\eta_P^2 = .21$].

The 3 x 3 x 3 x 3 ANOVA also revealed a main effect of kinematic level [$F(2,116) = 3.51$, $p < .05$, $\eta_P^2 = .06$]: participants gave the highest ratings at the K1 level [mean(SEM) = 3.50(.11)], followed by the K3 [mean(SEM) = 3.44(.11)], followed by the K1 level [mean(SEM) = 3.42(.11)].

This analysis revealed a significant main effect of rating [$F(2,116) = 3.592$, $p < .05$, $\eta_P^2 = .06$], with participants giving the highest sad ratings [mean(SEM) = 3.65(.13)], and comparable angry [mean(SEM) = 3.37(.15)] and happy ratings [mean(SEM) = 3.33(.13)] (regardless of which emotion was shown in the PLF).

Interactions:

This main effect of rating was qualified by an emotion x rating interaction [$F(4,232) = 489.95$, $p < .001$, $\eta_P^2 = .89$]. Whilst there was a main effect of rating for all three emotions (all

F > 179, all p < .001), the direction of the effect differed across all three emotions. As one might expect, for angry facial motion, angry ratings were highest [mean(SEM) = 5.59(.18)], followed by sad ratings [mean(SEM) = 3.41(.18)], followed by happy ratings [mean(SEM) = 1.85(.15)]. For happy facial motion, happy ratings were higher [mean(SEM) = 6.06(.16)] than angry [mean(SEM) = 1.77(.14)] and sad [mean(SEM) = 1.98(.13)] ratings (which were comparably low). Finally, for sad facial motion, sad ratings were highest [mean(SEM) = 5.57(.15)], followed by angry ratings [mean(SEM) = 2.77(.17)] and then happy ratings [mean(SEM) = 2.09(.15)].

In addition, we identified a spatial x rating interaction [F(4,232) = 64.26, p < .001, η_P^2 = .53]. Whilst there was a main effect of spatial for all three ratings (all F > 32, all p < .001), the direction of the effect differed for high and low arousal emotion ratings. Regardless of which emotion was shown, angry and happy ratings were highest at the S3 level [angry mean(SEM) = 4.19(.14); happy mean(SEM) = 3.62(.11)], followed by the S2 level [angry mean(SEM) = 3.33(.14); happy mean (SEM) = 3.48(.13)], followed by the S1 level [angry mean(SEM) = 2.61(.19); happy mean(SEM) = 2.89(.17)]. In contrast, regardless of which emotion was shown, sad ratings were highest at the S1 level [mean(SEM) = 4.17(.16)], intermediate at the S2 level [mean(SEM) = 3.49(.13)] and lowest at the S3 level [mean(SEM) = 3.30(.14)]

Our main analysis also revealed a kinematic x rating interaction [F(4,232) = 49.08, p < .001, η_P^2 = .46]. Whilst there was a main effect of spatial for all three ratings (all F > 11, all p < . 001), the direction of the effect across emotions. Regardless of which emotion was shown: angry ratings were highest at the K3 level [mean(SEM) = 3.74(.15)] and comparable at the K1 [mean(SEM) = 3.15(.17)] and K2 [mean(SEM) = 3.23(.14)] levels; happy ratings were highest at the K3 [mean(SEM) = 3.45(.13)] and K2 [mean(SEM) = 3.40(.13)] levels, and lower at the

K1 [mean(SEM) = 3.15(.13)] level; and sad ratings were highest at the K1 [mean(SEM) = 4.20(.14)], followed by the K2 [mean(SEM) = 3.62(.14)], followed by the K3 [mean(SEM) = 3.13(.14)] level.

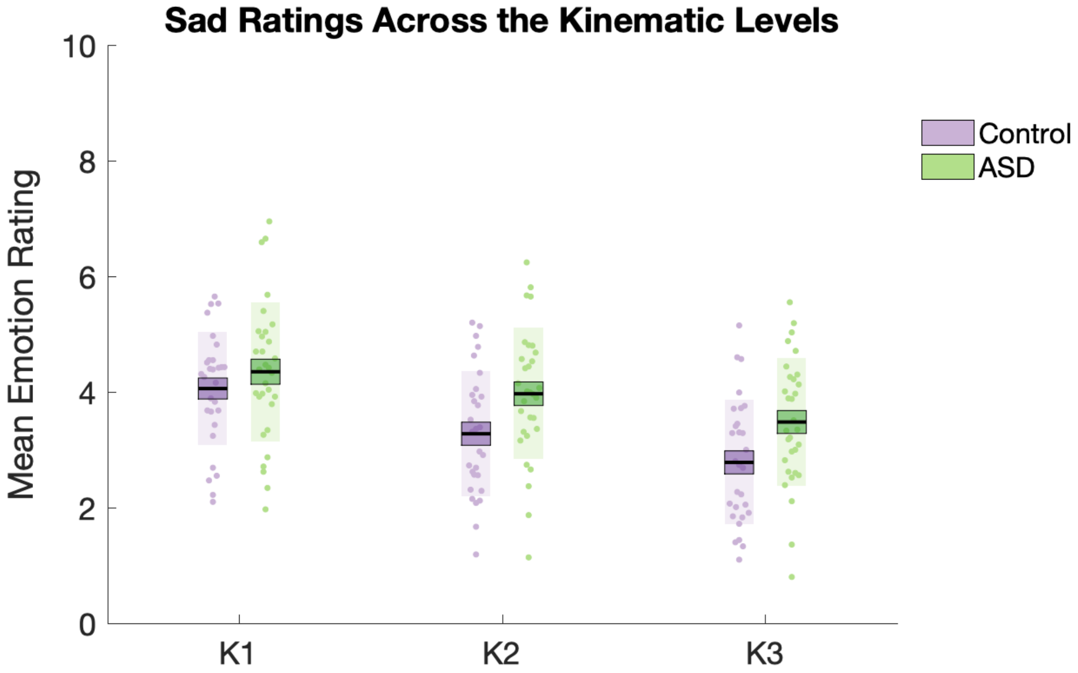
These interactions were further qualified by an emotion x spatial x rating interaction [$F(8,464) = 111.13$, $p < .001$, $\eta_P^2 = .66$]. Unpacking this interaction facilitated exploration of which specific emotion confusions were made as the PLF stimulus videos transitioned away from their typical spatial extent. Post-hoc repeated measures ANOVAs indicated that a spatial x rating interaction was present for all emotional videos (all $F > 98$, $p < .001$), but that this effect differed across these emotions. As the spatial level of angry facial motion decreased, they were rated as less angry [$F(2,116) = 247.43$, $p < .001$, $\eta_P^2 = .81$], and were more likely to be confused for happy [$F(2,116) = 21.96$, $p < .001$, $\eta_P^2 = .28$] and sad [$F(2,116) = 23.54$, $p < .001$, $\eta_P^2 = .29$]. In addition, as the spatial level of happy facial motion decreased, they were rated as less happy [$F(2,116) = 143.11$, $p < .001$, $\eta_P^2 = .71$], and were more likely to be confused for sad [$F(2,116) = 62.17$, $p < .001$, $\eta_P^2 = .52$] but not angry [$p = .061$]. In contrast, as the spatial level of sad facial motion increased, there were no differences in sad ratings [$p = .894$,] or happy ratings [$p = .256$], but they *were* more likely to be confused for angry [$F(2,116) = 40.54$, $p < .001$, $\eta_P^2 = .41$].

In addition, our main analysis found an emotion x kinematic x rating interaction [$F(8,464) = 12.02$, $p < .001$, $\eta_P^2 = .17$]. Unpacking this interaction facilitated exploration of which specific emotion confusions were made as the PLF stimulus videos transitioned away from their typical spatial extent. Post-hoc repeated measures ANOVAs indicated that whilst a kinematic x rating interaction was present for all emotional videos (all $F > 179$, $p < .001$), but that this effect differed across these emotions. Our analysis identified that as the speed of angry facial motion decreased, they were rated as less angry [$F(2,116) = 25.39$, $p < .001$, $\eta_P^2 = .30$], and were more likely to be confused for sad [$F(2,116) = 21.11$, $p < .001$, $\eta_P^2 = .27$]. Note that there were no differences in happy ratings for angry facial motion as speed changes [$p = .264$]. In addition, we found that as the speed of happy facial motion decreased, they were rated as less happy [$F(2,116) = 15.84$, $p < .001$, $\eta_P^2 = .21$], and were more likely to be confused for sad [$F(2,116) = 33.73$, $p < .001$, $\eta_P^2 = .37$]. Note that happy facial motion was more likely to be confused for angry at the K1 and K3 levels than at the K2 level [$F(2,116) = 4.37$, $p < .05$, $\eta_P^2 = .07$]. Finally, we found that as the speed of sad facial motion increased, they were rated as less sad [$F(2,116) = 58.18$, $p < .001$, $\eta_P^2 = .50$], and were more likely to be confused for angry [$F(2,116) = 30.56$, $p < .001$, $\eta_P^2 = .35$] and happy [$F(2,116) = 9.54$, $p < .001$, $\eta_P^2 = .14$]

In addition, we identified a kinematic x rating x group interaction [$F(4,232) = 2.79$, $p < .05$, $\eta_P^2 = .05$] and a spatial x kinematic x rating x group interaction [$F(8,464) = 2.76$, $p < .05$, $\eta_P^2 = .05$]. To unpack the first of these interactions, we conducted post-hoc 2 x 3 ANOVAs (group x kinematic) for each emotion rating. This analysis revealed a significant kinematic x group interaction for sad [$F(2,116) = 3.45$, $p < .05$, $\eta_P^2 = .06$], but not angry [$p = .110$] or happy [$p = .474$] ratings. Whilst there was a significant effect of the kinematic manipulation on sad ratings for both control [$F(2,56) = 46.98$, $p < .001$, $\eta_P^2 = .63$], and autistic [$F(2,60) = 26.85$, $p < .001$, $\eta_P^2 = .47$] participants, the effect of the kinematic manipulation was greater for controls (see Figure A1.3). In other words, regardless of what emotion was displayed, the sad ratings given by autistic (relative to control) participants were less affected by the kinematic manipulation. In our 2 x 3 ANOVA (group x kinematic) for sad ratings, we also identified a main effect of group, with autistic participants giving higher mean sad ratings (regardless of what emotion was displayed) [$t(58) = -2.11$, $p < .05$, mean difference = -0.56].

Figure A1.3.

Mean sad ratings given by autistic and control participants across the kinematic levels (averaging across the displayed emotions and spatial levels).

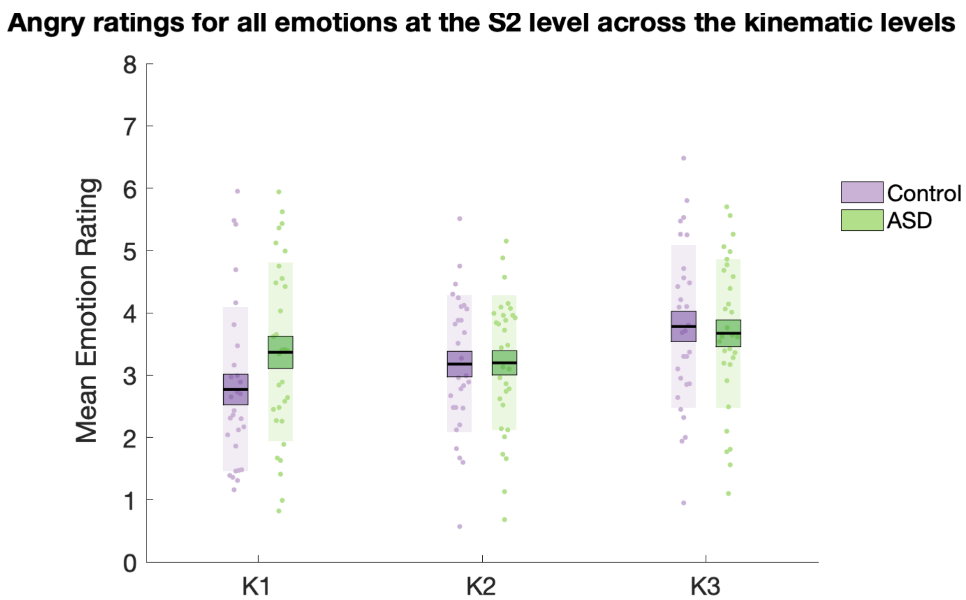


Note. The black line represents the mean, the shaded region represents the standard deviation, the coloured box represents 1 standard error around the mean and the dots are individual datapoints

In order to unpack the significant spatial x kinematic x rating x group interaction [$F(8,464) = 2.76$, $p < .05$, $\eta_P^2 = .05$], we conducted post-hoc 2 x 3 x 3 ANOVAs (group x kinematic x rating) for each spatial level. This revealed a significant group x kinematic x rating interaction at the S2 [$F(4,232) = 28.10$, $p < .001$, $\eta_P^2 = .06$] and S3 [$F(4,232) = 2.46$, $p < .05$, $\eta_P^2 = .04$] level, but not at the S1 [$p = .108$] level. We then completed post-hoc 2 x 3 ANOVAs (group x kinematic) for each rating at the S2 and S3 level. At the S2 level we found a significant kinematic x group interaction for angry [$F(2,116) = 4.55$, $p < .05$, $\eta_P^2 = .07$] and happy [$F(2,116) = 3.97$, $p < .05$, $\eta_P^2 = .06$] ratings but not sad [$p = .255$] ratings. Whilst there was a significant effect of the kinematic manipulation on angry ratings at the S2 level for control participants (regardless of which emotion was displayed) [$F(2,56) = 19.94$, $p < .001$, $\eta_P^2 = .42$], there was not a significant effect for autistic participants [$p = .054$] (see Figure A1.4) (however, there were no group differences in angry ratings at the S2 level across each of the kinematic levels). In addition, we found that whilst there was a significant effect of the kinematic manipulation on happy ratings at the S2 level for autistic participants [$F(2,60) = 8.88$, $p < .01$, $\eta_P^2 = .23$], there was not for controls [$p = .424$]. This difference in happy ratings across the kinematic levels led to a significant group difference, with autistic participants giving significantly higher happy ratings at the K3 [$t(58) = -2.85$, $p_{bonf} < .05$, mean difference = -0.80] but not K1 [$p = .421$] or K2 [$p = .178$] level (see Figure A1.5).

Figure A1.4.

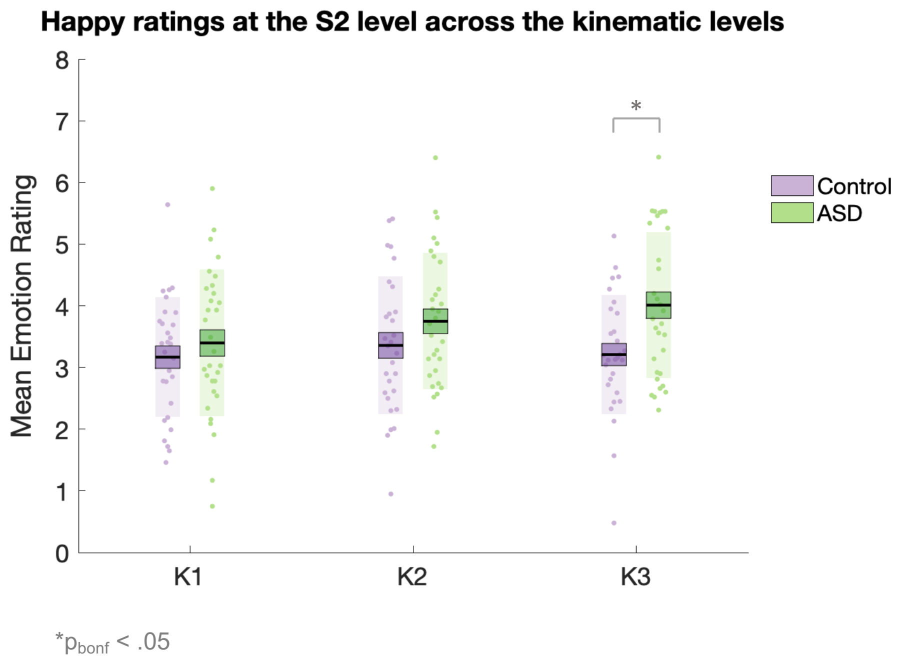
Mean angry ratings at the S2 level given by autistic and control participants across the kinematic levels (averaging across the displayed emotions).



Note. The black line represents the mean, the shaded region represents the standard deviation, the coloured box represents 1 standard error around the mean and the dots are individual datapoints

Figure A1.5.

Mean happy ratings at the S2 level given by autistic and control participants across the kinematic levels (averaging across the displayed emotions).

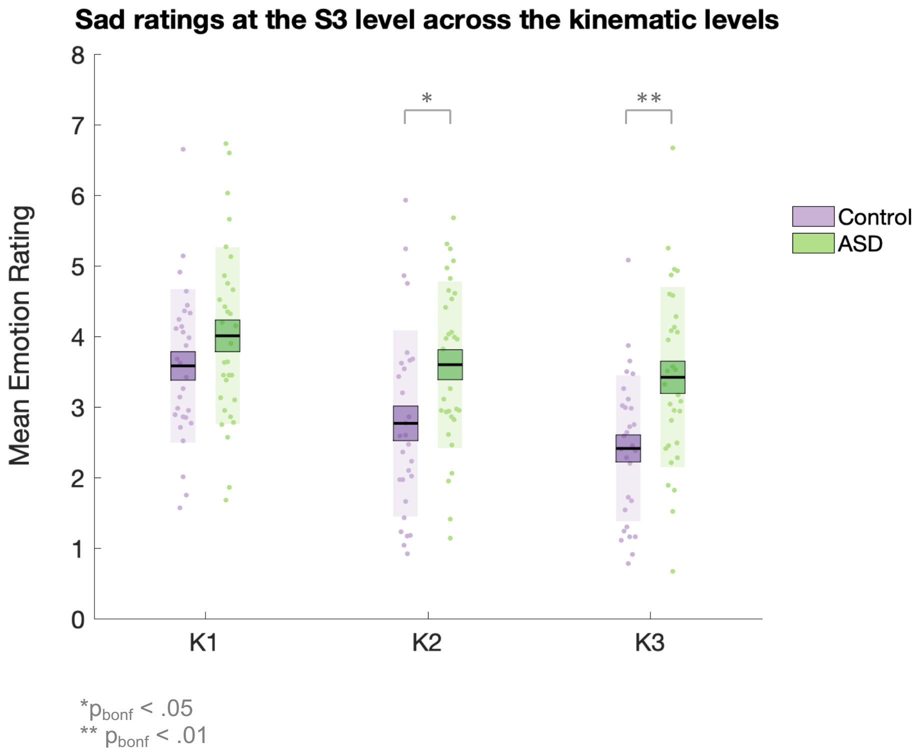


Note. The black line represents the mean, the shaded region represents the standard deviation, the coloured box represents 1 standard error around the mean and the dots are individual datapoints

At the S3 level, we found a significant kinematic x group interaction for sad [$F(2,116) = 3.80$, $p < .05$, $\eta_P^2 = .06$], but not angry [$p = .129$] or happy [$p = .177$] ratings. Whilst there was a significant effect of the kinematic manipulation on sad ratings at the S3 level for both control [$F(2,56) = 34.02$, $p < .001$, $\eta_P^2 = .55$], and autistic [$F(2,60) = 7.23$, $p < .01$, $\eta_P^2 = .19$] participants, the effect of the kinematic manipulation was greater for controls (see Figure A1.6). In other words, regardless of what emotion was displayed, at the S3 level, the sad ratings given by autistic (relative to control) participants were less affected by the kinematic manipulation. This smaller effect led to significant group differences in sad ratings, with autistic participants giving higher ratings (after Bonferroni-correction) at the K2 [$t(58) = -22.57$, $p_{bonf} < .05$, mean difference = -0.83] and K3 [$t(58) = -3.35$, $p_{bonf} < .01$, mean difference = -1.01] level, but not the K1 [p = .166] level. In our 2 x 3 ANOVA (group x kinematic) for sad ratings at the S3 level, we also identified a main effect of group, with autistic participants giving higher mean sad ratings at the S3 level (regardless of what emotion was displayed) [t(58) = -2.671, p < .05, mean difference = -0.75].

Figure A1.6.

Mean sad ratings at the S3 level given by autistic and control participants across the kinematic levels (averaging across the displayed emotions).



Note. The black line represents the mean, the shaded region represents the standard deviation, the coloured box represents 1 standard error around the mean and the dots are individual datapoints

Appendix 2

Supplementary Materials for Chapter 3

Comparing internal representations of facial expression kinematics between autistic and non-autistic adults

Connor T. Keating, Sophie Sowden, and Jennifer L. Cook

(Published in *Autism Research*)

Reference: Keating CT, Sowden S, Cook JL. Comparing internal representations of facial expression kinematics between autistic and non-autistic adults. Autism Research. 2022 Mar;15(3):493-506. https://doi.org/10.1002/aur.2642

Appendix 2.1 – Full and partial face PLFs

Access examples of full-face and partial-face PLFs at: https://tinyurl.com/keatingthesis

Appendix 2.2 – Participants' ethnicities in Chapter 3

Table A2.1.

Ethnicity data for autistic and non-autistic participants.

Ethnic Group	Autistic (N=25)	Non-autistic (N=25)
White English/Welsh/Scottish/Northern Irish/British	21	3
White Hungarian/Greek	1	0
White European	1	2
Mixed/Multiple Ethnic Groups- White and Black Caribbean	1	0
White Polish	0	6
White Italian	0	3
White Portuguese	0	2
White/Caucasian	0	2
White Slavic	0	1
White Albanian	0	1
Black African	0	1
Asian Pakistani	0	1
Asian Indian	0	1
Mixed/Multiple Ethnic Groups- White and Asian	0	1
Mixed/Multiple Ethnic Groups- Other	0	1
Prefer not to say	1	0

Appendix 3

Supplementary Materials for Chapter 4

The Inside Out Model of Emotion Recognition: How the Shape of One's Internal Emotional Landscape Influences the Recognition of Others' Emotions

Connor T. Keating and Jennifer L. Cook

(Published in *Scientific Reports*)

Reference: Keating CT, Cook JL. The inside out model of emotion recognition: How the shape of one's internal emotional landscape influences the recognition of others' Emotions. Scientific Reports. 2023 Dec 6;13(1):21490. https://doi.org/10.1038/s41598-023-48469-8

Appendix 3.1 - The effect of emotion on emotional precision and representational precision, and the effect of emotion pair on distance between clusters and distance between representations.

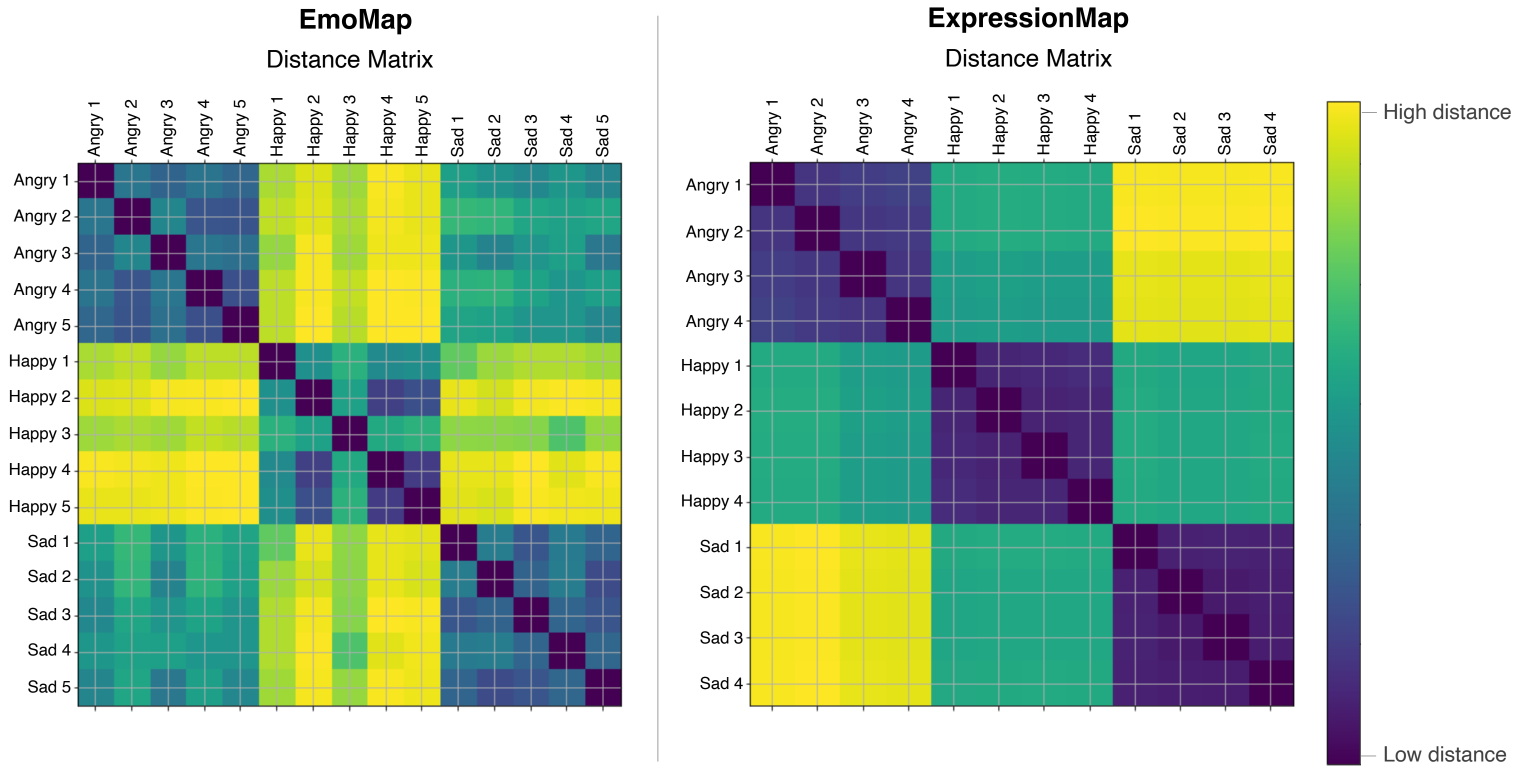
To assess whether the precision of emotional experiences and visual emotion representations differed as a function of emotion, we constructed two linear mixed effects models. In the first model, emotional precision was the outcome variable; in the second, representational precision was the outcome variable. In both models, emotion (angry, happy, sad) was included as a predictor and subject number was modelled as a random intercept. Whilst representational precision differed as a function of emotion [original sample: $F(2,194) = 86.63$, $p < .001$; replication sample: $F(2,384) = 252.44$, $p < .001$], emotional precision did not [$p > .05$]. Across both samples, representational precision was highest for sadness [original sample mean (SEM) = -0.51(0.03); replication sample mean(SEM) = -0.49(0.02)], followed by happiness [original sample mean(SEM) = -0.63(0.03); replication sample mean(SEM) = -0.62(0.02)], followed by anger [original sample mean(SEM) = -0.88(0.04), replication sample mean(SEM) = -0.88(0.03)].

Next, we aimed to assess whether distance between emotion clusters and distance between representations differed as a function of emotion pair. Therefore, we constructed two linear mixed effects models predicting distance between clusters, and distance between representations, respectively, with emotion pair (angry-happy, angry-sad, happy-sad), and with subject number as a random intercept. There was a significant main effect of emotion pair for distance between emotion clusters [$F(2,540) = 487.69$, $p < .001$]: there were smaller distances between anger and sadness [mean distance (SEM) = 14.39(0.21)], than happiness and anger [mean distance (SEM) = 20.79(0.29)], and happiness and sadness [mean distance (SEM) = 20.70(0.29)] in this experience domain. These results suggest that experiences of anger and sadness (i.e., same-valence emotions) are more similar than experiences of happiness and anger, and happiness and sadness (i.e., opposite-valence emotions).

In addition, we found a significant main effect of emotion pair for distance between representations [$F(2,384) = 180.44$, $p < .001$]: there were smaller distances between representations for anger and happiness [mean(SEM) = 1.16(0.05) pixels/frame] and happiness and sadness [mean(SEM) = 1.18(0.04) pixels/frame], than for anger and sadness [mean(SEM) = 2.23(0.07) pixels/frame] in this speed domain. These results are logical: previous findings suggest that visual representations of anger are typically fastest, followed by happiness, followed by sadness[449]. Since happy expressions comprise an intermediate, they are most likely to overlap with both anger and sadness. To illustrate these effects, we computed a distance (i.e., dissimilarity) matrix for both EmoMap and ExpressionMap (see Figure A3.1). In this matrix, you can see that there are greater distances between experiences of anger and happiness, and smaller distances between experiences of anger and sadness in EmoMap. Conversely, there are smaller distances between visual representations for anger and happiness, and larger distances between representations for anger and sadness in ExpressionMap.

Figure A3.1.

Two distance matrices illustrating the mean distances between emotional experiences for anger, happiness and sadness (for five images each; left) and the mean distances between visual representations of anger, happiness and sadness (for four repetitions each; right).



Appendix 3.2 - Building the Inside Out Model of Emotion Recognition

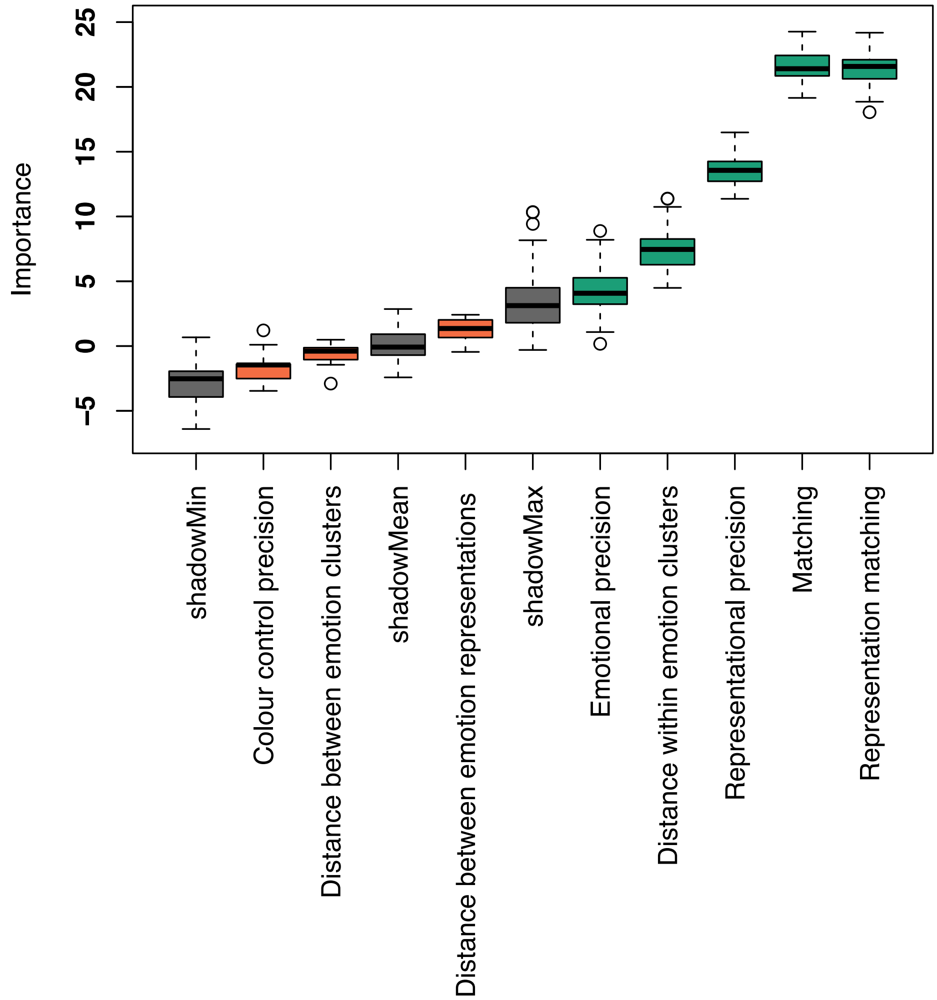
Determining which variables are important for emotion recognition

To assess the contribution of both EmoMap and ExpressionMap variables to emotion recognition we focused on the 193 participants that completed both tasks. First, since we had a large number of potential variables of interest, we determined their relative importance with respect to emotion recognition using a random forest analysis[431]. Our random forests analysis[431] employed the Boruta[432] wrapper algorithm (version 7.7.0) which trains a random forest regression on all predictors, as well as their shuffled copies (known as "shadow features"),and classifies a variable as important when its importance score is higher than the highest importance score for a shadow feature. Our predictor variables included mean emotional precision, colour (control) precision, mean distance between emotion clusters, mean distance within emotion clusters, mean representational precision, matching difficulty, mean distance between emotion representations, and representation matching. 'Representation matching' was computed by multiplying the representational precision scores for angry, happy and sad expressions with their corresponding matching difficulty scores (e.g., angry representational precision x angry matching difficulty; happy representational precision x happy matching difficulty; sad representational precision x sad matching difficulty). Higher representation matching scores indicate superior representational precision, matching ability, or both.

This analysis revealed that, of the eight variables, five were confirmed *important*, and three were confirmed *unimportant.* Figure A3.2 illustrates that representation matching [median importance score (MIS) = 21.58], matching difficulty [MIS = 21.40], representational precision [MIS = 13.56], distance between emotion clusters [MIS = 7.46], and emotional precision [MIS = 4.08] were classified as important (green) for emotion recognition. Mean distance between emotion representations [MIS = 1.36], mean distance within emotion clusters [MIS = -0.39], and colour control precision [MIS = -1.46] were classified as unimportant (red).

Figure A3.2.

Random forest variable importance scores.



Note. Variable importance scores for all eight variables included in the Boruta random forest regression model, displayed as boxplots. Box edges correspond to the interquartile range (IQR); whiskers represent 1.5 × IQR distance from box edges; circles denote outliers. Box colour reflects the decision made by the algorithm: Green = confirmed important, yellow = tentative, red = rejected; grey = shadow features – shadowMin, shadowMean, shadowMax (minimum, mean and maximum variable importance scores of shadow features, respectively).

Constructing the most mathematically plausible structural equation model

Following this, we employed structural equation modelling (SEM) to build a mathematically plausible mechanistic model of the pathways linking internal emotional experiences with emotion recognition in the outside world. To achieve this, we first estimated latent constructs from their manifest indicator variables while accurately isolating any measurement error[580]. The latent construct of emotional precision was estimated using emotional precision EmoMap scores for anger, happiness, and sadness respectively; distance between emotion clusters was estimated using the EmoMap distances between the angry and happy, angry and sad, and happy and sad clusters respectively; representation matching was estimated using ExpressionMap scores for the interaction between representational precision and matching for angry expressions, representational precision and matching for happy expressions, and finally representational precision and matching for sad expressions; emotion recognition accuracy was estimated using accuracy scores from the PLF Emotion Recognition Task for angry, happy and sad expressions respectively. Due to failure of model convergence as a result of high collinearity between manifest variables [correlation for the distance between angry and happy, and angry and sad representations: $R = .725$, $p < .005$], the latent construct distance between representations was estimated using the distance between happy and sad, and angry and sad representations only (i.e., the distance angry and happy representations was not used to estimate distance between representations).

Subsequently, we modelled the structural (direct and indirect) paths between latent constructs. To this end, we added variables classified as "important" in our random forests analysis into a structural equation model predicting emotion recognition accuracy, sequentially (starting with the most important variable), until there was a) no longer a significant improvement (or our goodness of fit index exceeded the specified threshold), or b) our goodness of fit indices dropped below threshold [RMSEA > 0.08; SRMR > 0.08; CFI < 0.95)[581]. We also included paths for variables that were discovered to be significant predictors in our previous analyses (e.g., predicting emotional precision with NVR, predicting distance between clusters with TAS). Given that our data contained normally distributed continuous variables, we used a maximum likelihood estimator across all structural equation models. Within our first full model, there were significant direct effects of distance between emotion clusters [z = 3.96, *b* = 0.32, p < .001] and representation matching [z = 6.68, *b* = 0.69, p < .001] on emotion recognition accuracy. In addition, mediation analyses to test for the presence of indirect effects on accuracy revealed that emotional precision contributed to accuracy [z = 2.11, *b* = 0.51, p < .05] by influencing the representational precision x matching interaction [direct effect: z = 2.22, *b* = 0.73, p < .05]. Furthermore, serial mediation analyses identified that non-verbal reasoning exerted an indirect effect on accuracy [z = 4.99, *b* = 0.33, p < .001] by influencing emotional precision [direct effect: z = 2.24, *b* = 0.65, p < .05], which contributed to the representational x matching interaction [direct effect: z = 2.22, *b* = 0.73, p < .05], which predicted emotion recognition [direct effect: z = 6.70, *b* = 0.70, p < .001]. Finally, we identified that alexithymia exerted an indirect effect on emotion recognition accuracy [z = -2.23, *b* = -0.06, p <.05] by influencing distance between emotion clusters [z = -2.68, *b* = -0.19, p < .01], which in turn contributed to distance between emotion representations [direct effect: z = 2.60, *b* = 0.26, p < .01]. Fit indices demonstrated that this model was a good fit for the data [RMSEA = 0.057; SRMR = 0.076; CFI = 0.952].

A significant strength of structural equation modelling is that it provides the opportunity to reverse path directions to establish mathematically plausible directions of causality[582]. We constructed a series of structural equation models in which the direction of one (and only one) of the paths was reversed and calculated Bayesian Information Criterion (BIC) difference scores by subtracting the sample size adjusted BIC scores of our final model from the 'reversed models'. BIC difference scores between 2 and 6 reflect moderate evidence, between 6 and 10 reflect strong evidence, and above 10 reflect very strong evidence, for model improvement[583]. There was *very strong* evidence that our model was better than the reversed model in three instances (representation matching → emotional precision: BIC difference = 50.953; accuracy → representation matching: BIC difference = 16.219; distance between clusters → TAS: BIC difference = 1496.51). However, interestingly, there was very strong evidence that the reverse direction was more plausible in one instance (emotional precision → non-verbal reasoning: BIC difference = -184.898). Finally, our model and the reversed model were comparable in two instances (emotion recognition accuracy → distance between clusters: BIC difference = 0.953; distance between emotion representations → distance between clusters: -1.841; see Table A3.1). Following this, we constructed a structural equation model in which we included the path directions that were mathematically most plausible (i.e., reversed one of the paths such that it was emotional precision → non-verbal reasoning). For paths in which neither direction was more plausible, we modelled both path directions (i.e., distance between clusters → emotion recognition accuracy, and emotion recognition accuracy → distance between clusters; distance between emotion clusters → distance between emotion representations, and distance between emotion representations → distance between emotion clusters) in direct feedback loops.

Table A3.1.

A table showing the difference in Bayesian Information Criterion (BIC) scores between our final structural equation model and models in which each of the paths were reversed.

Reversed Path	BIC Difference	Preferred Model	Strength of evidence
Distance between clusters → TAS	1496.51	Original	Very strong
Representational Precision x Matching → Emotional Precision	50.953	Original	Very strong
Accuracy → Representational Precision x Matching	16.219	Original	Very strong
Accuracy → Distance between clusters	0.953	Neither	No evidence
Distance between representations → Distance between clusters	-1.841	Neither	No evidence
Emotional Precision → NVR	-184.898	Reversed	Very strong

Notably, this model revealed that only one of these bidirectional feedback loops were significant: there were significant direct effects of distance between emotion clusters on accuracy [$z = 2.26$, $b = 0.20$, $p < .05$], and accuracy on distance between emotion clusters [$z = 2.65$, $b = 0.27$, $p < .01$], thus confirming a bidirectional feedback loop between these variables. By contrast, there was a marginally significant direct effect of distance between representations on distance between emotion clusters [$z = 1.75$, $b = 0.54$, $p = .081$], but not distance between emotion clusters on distance between representations [$p = .396$]. Therefore, we constructed one final structural equation model with the most mathematically plausible path directions, including a bidirectional feedback loop between distance between emotion clusters and accuracy, and a unidirectional path from distance between representations to distance between emotion clusters. There was very strong evidence that our final model, which could account for 60.8% of the variance in emotion recognition accuracy, was more mathematically plausible than our original model (BIC difference = 192.427). The information about our final structural equation model is reported in the Results section.

Appendix 3.3 – Inter-relationships between the variables in our final structural equation model

Table A3.2.

A table showing the degree of correlation between all of the variables in our final structural equation model.

	1	2	3	4	5	6	7
1. Accuracy	1.000						
2. Distance between clusters	0.412	1.000					
3. Emotional precision	0.515	0.271	1.000				
4. Representation Matching	0.724	0.170	0.434	1.000			
5. Distance between representations	0.002	0.007	0.011	-0.006	1.000		
6. NVR	0.367	0.033	0.347	0.475	0.000	1.000	
7. TAS	-0.269	-0.192	-0.433	-0.196	0.002	-0.117	1.000

Appendix 3.4 - Partial correlations controlling for self-reported effort

At the end of the study, we asked participants to report how much effort they put in while completing the tasks on a scale from 0 (no effort at all) to 10 (maximum effort). In order to elicit honest responses, we informed participants that they would still be renumerated for their time irrespective of their answer, and emphasised the importance of giving truthful responses.

In order to assess whether our variables of interest were associated with self-reported effort, we ran a series of simple correlations (see Table A3.2). This revealed that self-reported effort was not associated with emotional precision, representational precision, distance between representations, matching deviation scores, or representation matching [all $p > .05$]. However, there were small-moderate correlations between self-reported effort and distance between clusters [$R = .263$, $p < .001$] and emotion recognition accuracy [$R = .236$, $p = .001$].

Table A3.3.

A table showing the Pearson correlations between self-reported effort and our variables of interest. Note that these p values are not corrected for multiple comparisons.

	Emotional precision	Distance between clusters	Representational precision	Distance between representations	Matching deviation	Representation matching	Emotion recognition accuracy
Effort	R = -.065 p = .368	R = .272* p < .001	R = .071 p = .330	R = .035 p = .631	R = -.126 p = .081	R = .110 p = .129	R = .236* p = .001

Therefore, in order to determine whether self-reported effort underpinned the relationships between our variables of interest, we conducted a series of partial correlations controlling for self-reported effort. Across all analyses, significant relationships were identified even after controlling for self-reported effort: the relationship between emotion recognition accuracy and distance between clusters [$R = .260$, $p_{bonf} = .002$], emotion recognition accuracy and the representational precision x matching interaction [$R = .549$, $p_{bonf} < .001$], the representational precision x matching interaction and emotional precision [R = .251, p_{bonf} = .003], emotional precision and non-verbal reasoning [R = .228, p_{bonf} = .009], distance between representations and distance between clusters [R = .221, p_{bonf} = .013], and distance between clusters and alexithymia [R = -.199, p_{bonf} = .036], all held after Bonferroni-correction (correcting for six tests).

Appendix 3.5 – The effect of sex on our pattern of results

Since our samples were unbalanced with regards to sex, we conducted a series of analyses to determine whether sex moderated any of our primary effects. The general pattern of results was very similar to that reported in the main manuscript (see full results below).

First, we conducted analyses assessing the extent to which the contribution of alexithymia to distance between and within clusters was moderated by sex. To test this, we constructed two linear mixed effects models with distance between clusters and distance within clusters as the outcome variables, TAS, sex, and the TAS x sex interaction as predictors, and with subject number as a random intercept. For distance *between* clusters, there was a significant effect of TAS [$F(1,267) = -5.24$, $p < .05$] that was not moderated by sex [$p = .231$]. As found previously, those higher in alexithymia had smaller distances between their emotion clusters. For distance *within* clusters, there was a significant TAS x sex interaction [$F(1,267) = -4.80$, $p < .05$]. Unpacking this interaction revealed that alexithymia was a significant negative predictor of distance within clusters for males [$F(1,66) = 5.20$, $p <.05$] but not females [$p = .484$]. It is important to note that this finding does not significantly change our main pattern of results; for our final structural equation model, TAS is modelled as a significant predictor of distance *between* clusters, while distance within clusters is not included in the model.

Next, we aimed to assess whether sex moderated the effect we found of distance between clusters, and distance within clusters on emotional precision. Therefore, we constructed a linear mixed model predicting emotional precision with distance between clusters, distance within clusters, their interactions with sex, and sex. As reported in the main manuscript, distance between clusters was a significant positive predictor [$F(1,265) = 8.45$, $p <.01$],and distance within clusters was a significant negative predictor [$F(1,265) = -9.84$, $p<.01$] of emotional precision. There were no significant interactions with sex [$p > .05$], thus suggesting that these predictive relationships exist for both males and females.

Following this, we aimed to verify whether sex moderated the effect of representational precision on emotion recognition accuracy. Thus, we constructed a linear mixed effects model of emotion recognition accuracy as a function of mean representational precision, sex, and the representational precision x sex interaction. Across both samples, there was a significant effect of representational precision on emotion recognition accuracy [original sample: $F(1,94) = 5.07$, $p < .05$; replication sample: $F(1,189) = 42.95$, $p < .001$], that was not moderated by sex [all $p > .05$]. These results suggest that, for both males and females, representational precision significantly contributes to emotion recognition accuracy.

Next, we aimed to assess whether sex moderated the effect of the representational precision x matching interaction on emotion recognition accuracy. To fulfil this aim, we conducted a linear mixed effects model predicting emotion recognition accuracy with representational precision, matching difficulty, the representational precision x matching interaction, and the interactions of these variables with sex. In line with the results reported in the main manuscript, this identified a significant representational precision x matching interaction [$F(1,185) = 12.19$, $p < .001$], that was not moderated by sex [$p > .05$]. Unpacking this interaction, revealed that representational precision was only a significant predictor for those with a lower ability to match [$F(1,92) = 17.53$, $p < .001$], and not those with a higher ability to match [$p > .05$]. Again, these effects were not moderated by sex. Together, these results suggest that, for both males and females, when individuals struggle to match two expressions, representational precision plays an important role.

Following this, we aimed to determine whether the relationships we discovered between how individuals feel "on the inside" and how they expect expressions to look "on the outside" were moderated by sex. First, we assessed whether the contribution of emotional precision to representational precision was moderated by sex using a linear mixed effects model. As found previously, emotional precision was a significant predictor of representational precision [$F(1,189) = 12.46$, $p < .001$]. There was no emotional precision x sex interaction [$p > .05$], thus indicating that for both males and females, having precise emotional experiences is associated with precise visual representations of emotion. Second, we examined whether the contribution of distance between clusters to distance between representations was moderated by sex using a linear mixed model. This identified that, distance between clusters was a significant predictor of distance between representations [$F(<1189) = 4.97$, $p < .05$]. Importantly, this effect was not moderated by sex [$p > .05$]. Thus, for both males and females, having more distinct experiences of emotion predicts more distinct visual representations of emotion.

Next, we aimed to confirm whether the paths stipulated in our final structural equation model were present for both males and females. Therefore, we attempted to conduct independent structural equation models in each group. However, due to the sample of males being relatively small ($N = 41$), the model conducted in this sample did not converge. Therefore, it was not possible to assess the relationships between our variables of interest simultaneously in one model (for males). Nevertheless, it is reassuring that the evidence from our previous models points towards a precision component that is not moderated by sex: we found significant relationships between emotional precision and representational precision, representational precision and accuracy, and the representational x matching interaction and accuracy, independent of sex. We have also identified some evidence for the differentiation component existing for both male and females: we found significant relationships between alexithymia and distance between clusters, and distance between clusters and distance between representations, that are not moderated by sex. Further research, which employs larger samples of males, is necessary to determine whether the same mechanisms are involved in emotion recognition for both males and females.

Appendix 3.6 – Participants' ethnicity information in Chapter 4

Table A3.4.

A table displaying the ethnicities of participants from Experiment 1.

Ethnicity	Frequency
Afghan	1
Arab	2
Asian Bangladeshi	2
Asian British	11
Asian Filipino	1
Asian HongKonger	1
Asian Indian	8
Asian Indonesian	1
Asian Nepali	1
Asian Pakistani	10
Asian Sri Lankan	1
Asian British Pakistani	1
Black African	37
Black African and Caribbean	1
Black British	3
Black Caribbean	1
Black/African/Caribbean background: Somali	1
Chinese	18
Cypriot	1
Hispanic	1
Mixed/Multiple ethnic groups- Asian/African	1
Mixed/Multiple ethnic groups- Indian/Bangladeshi/Iraqi	1
Mixed/Multiple ethnic groups- Middle East/Israeli	1
Mixed/Multiple ethnic groups- Portuguese/Arab	1

Mixed/Multiple ethnic groups- Latin American	1
Mixed/Multiple ethnic groups- White and Asian	2
Mixed/Multiple ethnic groups- White and Black African	2
White Albanian	1
White American	2
White Austrian	1
White Baltic Finnic	1
White Belgian	1
White Bulgarian	1
White Caucasian	1
White Czech	1
White Dutch	1
White Eastern European	2
White English/Welsh/Scottish/Northern Irish/British	101
White English/White Eastern European	1
White Estonian	1
White European	5
White French	1
White German	1
White Hispanic	2
White Iberian	1
White Irish	1
White Italian	1
White Latin	1
White Latvian	1
White Mediterranean	1
White Northern European	1
White Polish	3
White Portuguese	5
White Romanian	2
White Slaav	3
White South African	2
White Turkish	1
Not disclosed	12
Total	**271**

Table A3.5.

A table displaying the ethnicities of participants from Experiment 2, Original Sample.

Ethnicity	Frequency
Asian Bangladeshi	1
Asian Indian	3
Asian Korean	1
Asian Pakistani	1
Black African	3
Black British	1
Black Caribbean	1

Chinese	1
Mixed/Multiple ethnic groups- White and Asian	2
Mixed/Multiple ethnic groups- White and Black Caribbean	1
White Caucasian	1
White English/Welsh/Scottish/Northern Irish/British	63
White European	5
White German	1
White Irish	4
White Italian	1
White Lithuanian	1
White Mixed European	1
White Polish	2
White Portuguese	3
Not disclosed	1
Total	**98**

Table A3.6.

A table displaying the ethnicities of participants from Experiment 2, Replication Sample.

Ethnicity	Frequency
Afghan	1
Arab	1
Asian Bangladeshi	2
Asian British	7
Asian HongKonger	1
Asian Indian	6
Asian Indonesian	1
Asian Nepali	1
Asian Pakistani	6
Asian Sri Lankan	1
Asian: British Pakistani	1
Black African	24
Black African and Caribbean	1
Black British	3
Black Caribbean	1
Black/African/Caribbean background: Somali	1
Chinese	12
Cypriot	1
Mixed/Multiple ethnic groups- Asian/A frican	1
Mixed/Multiple ethnic groups- Indian/Bangladeshi/Iraqi	1
Mixed/Multiple ethnic groups- Portuguese/Arab	1
Mixed/Multiple ethnic groups- Latin American	1
Mixed/Multiple ethnic groups- White and Asian	1
Mixed/Multiple ethnic groups- White and Black African	2

White Albanian	1
White American	1
White Baltic Finnic	1
White Belgian	1
White Bulgarian	1
White Caucasian	1
White Czech	1
White English/Welsh/Scottish/Northern Irish/British	81
White Estonian	1
White European	3
White French	1
White Hispanic	1
White Irish	1
White Italian	1
White Latvian	1
White Northern European	1
White Polish	3
White Portuguese	3
White Romanian	2
White Slaav	2
White South African	1
Not disclosed	6
Total	**193**

Appendix 3.7 - Pilot Study (N = 20)

In the second part of the EmoMap paradigm, which assesses emotional precision, there are 11 images that induce anger, happiness and sadness respectively (33 images in total). If we were to include all of these images in the first part of the EmoMap task, which assesses emotion differentiation, participants would be required to complete 528 trials (one trial for every image pair combination). Given that providing a similarity rating for each image pair combination typically takes 15 seconds, the duration of this task would be over two hours. Since this task is part of a wider battery investigating the experience, visualization and recognition of emotion, it is crucial that the task is shorter in length. Therefore, in a pilot study we aimed to identify five images for each emotion (15 images in total) that were effective at inducing the target emotion, and generated well-differentiated emotion clusters. By selecting five images per emotion, we knew that there would be 105 image pair combinations and therefore the task would take approximately 25 minutes to complete.

To fulfil our aim, we recruited 20 participants from Prolific (participant demographics shown in Table A3.6) to complete a longer version of the first part of the EmoMap task that included all 11 possible images for each emotion. In this task, on each trial participants viewed pairs of emotional images and were required to rate how similar the emotions evoked by the images were (see full task description in the main manuscript). To map the shape and size of participants' internal emotional landscapes, similarity ratings were transformed into Euclidean distance scores through multidimensional scaling (using the Scikit-learn library in Python). These distance scores were then used to plot the internal emotional landscape (see Figure A3.3). After completing the first part of the EmoMap task, participants also completed the 'Emotion Label' task. In this task, on each trial participants viewed one of the images they had seen previously and were then required to state the emotion they felt most strongly when looking at this image.

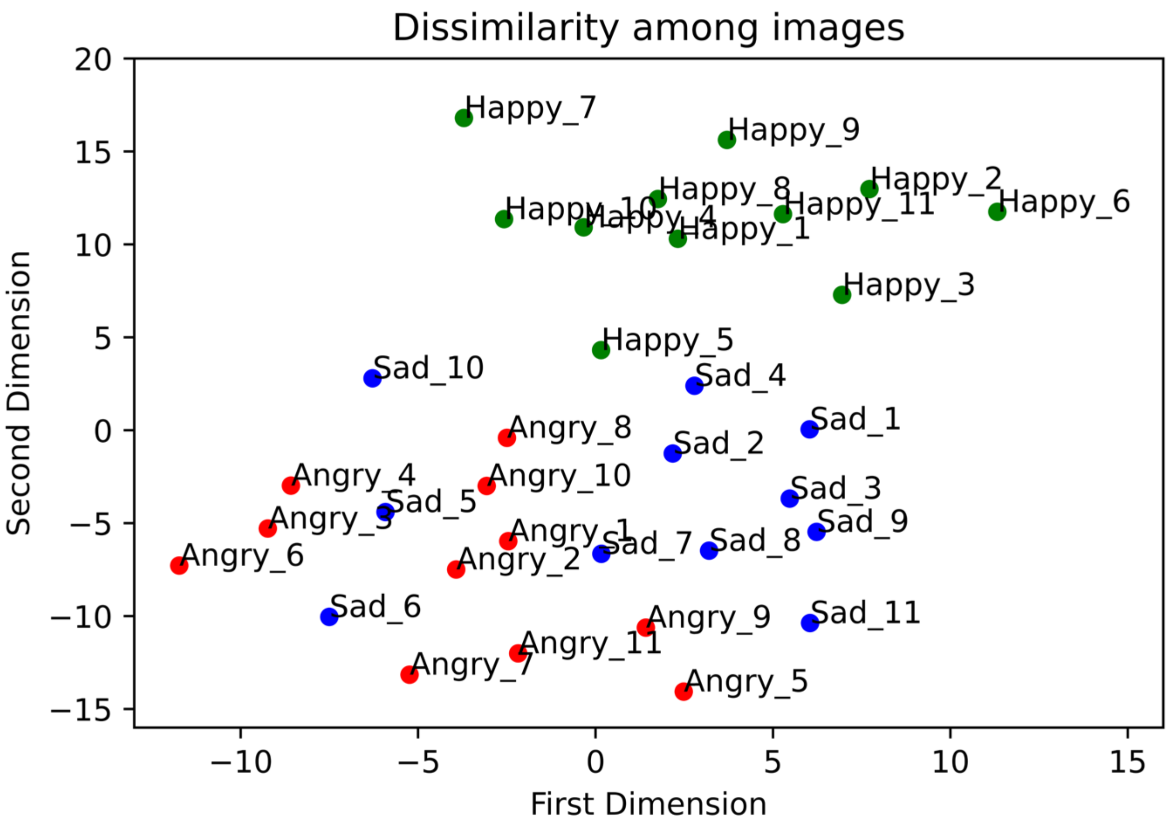
Table A3.7.

Means and standard deviations of participant characteristics. In the column on the right-hand side, means are followed by standard deviation in parentheses.

Variable	Participants (N = 20)
Sex	9 Male, 11 Female
Age	32.35(11.74)
AQ-50	22.40(7.23)
TAS-20	50.50(16.04)

Figure A3.3.

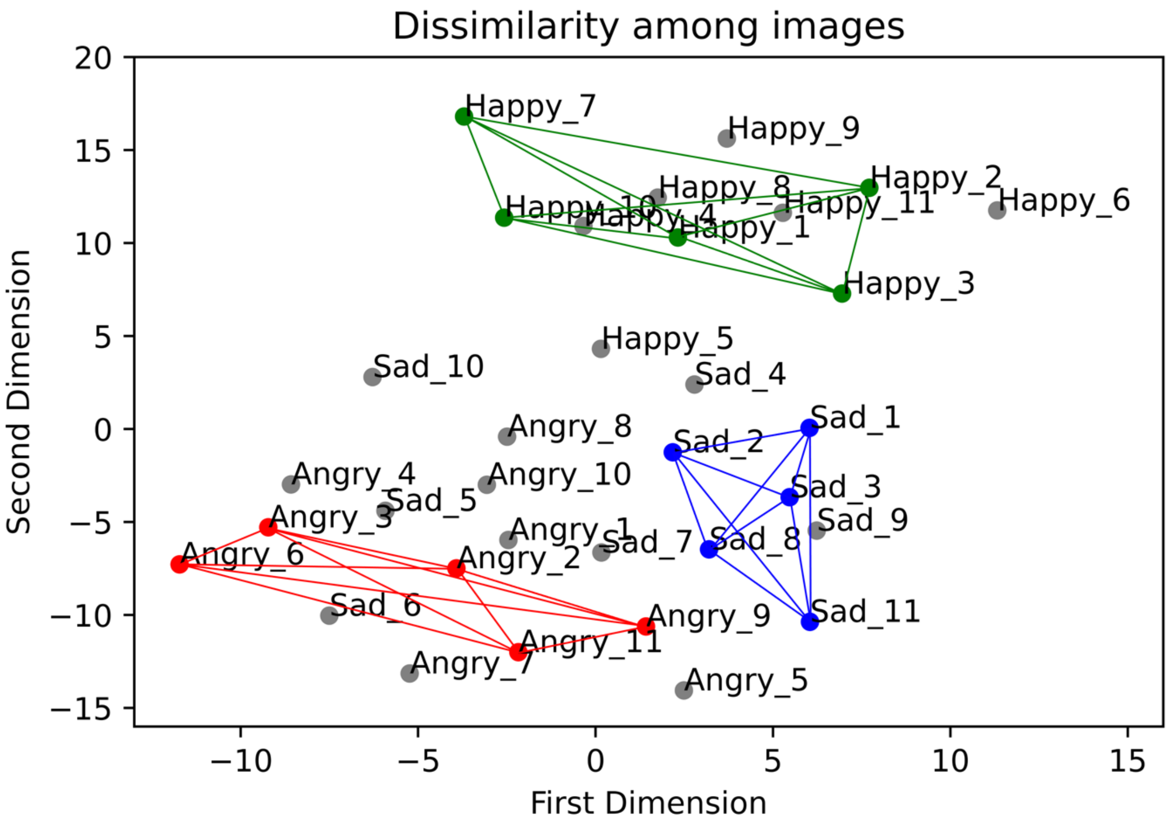
A diagram displaying the aggregated internal emotional landscape across all pilot study participants.



Following creation of the multidimensional scaling plot, we selected five images for each emotion based on the following criteria. Firstly, all of the selected images were rated as inducing the target emotion more than any other emotion in Riegel et al[430] (e.g., for images selected to induce anger, the intensity rating for anger was higher than for all other emotions). Secondly, the selected images formed an emotion cluster that was visually distinct from the other clusters (this led to us exclude Sad_5, and Sad_6 as these sad images were close to many of the angry images in the map, and received relatively high angry ratings in Riegel et al., 2016). Thirdly, the images were freely labelled as inducing the target emotion (or a similar emotion, i.e., anger, frustration) by a higher number of participants than for unselected images on our independent emotion labelling task. Finally, we ensured that there was a similar mean intensity rating and standard deviation of intensity ratings for each emotion cluster based on the ratings from Riegel et al[430] [angry mean(SD) = 4.05(0.73); happy mean(SD) = 4.00(0.78); sad mean(SD) = 3.75(0.67)]. By doing so, it would not be the case that, for instance, there were larger distances within one emotion over another because there was a large difference in intensity ratings (and therefore the experience of emotion was less similar). The selected images for each cluster are shown in colour (see Figure A3.4).

Figure A3.4.

A diagram displaying the aggregated internal emotional landscape of pilot study participants.



Note. The images that were selected for the short version of the similarity task are in colour, and the images that were not selected are in grey.

Appendix 4

Supplementary Materials for Chapter 5

Autistic adults exhibit highly precise representations of others' emotions but a reduced influence of emotion representations on emotion recognition accuracy

Connor T. Keating, Eri Ichijo, and Jennifer L. Cook

(Published in *Scientific Reports*)

Reference: Keating CT, Ichijo E, Cook JL. Autistic adults exhibit highly precise representations of others' emotions but a reduced influence of emotion representations on emotion recognition accuracy. Scientific Reports. 2023 Jul 22;13(1):11875. https://doi.org/10.1038/s41598-023-39070-0

Appendix 4.1 - The full results from our linear mixed effects model of accuracy

As stated in the main manuscript, we constructed a linear mixed effects model of emotion recognition accuracy (as measured by the PLF emotion recognition task) as a function of emotion (angry, happy, sad), spatial level (50%, 100%, 150% spatial exaggeration), kinematic level (50%, 100%, 150% speed), group (autistic, non-autistic), the interaction between these variables (independent variables), age, sex, non-verbal reasoning, and alexithymia (control variables) as predictors, and subject number as a random intercept. This analysis revealed a significant main effects of emotion [$F(2,2318) = 112.12$, $p < .001$], spatial level [$F(1,2318) = 162.37$, $p < .001$], and kinematic level [$F(1,2318) = 10.60$, $p = .001$], which were qualified by emotion x spatial [$F(2,2318) = 36.75$, $p < .001$], and emotion x kinematic [$F(2,2318) = 18.60$, $p < .001$] interactions. Unpacking the emotion x spatial interaction demonstrated that whilst emotion recognition accuracy improved with *increasing* spatial exaggeration for anger and happiness, it improved with *decreasing* spatial exaggeration for sadness (as in Sowden et al., 2021). Similarly, unpacking the emotion x kinematic interaction revealed that whilst emotion recognition accuracy improved with *increasing* speed for anger and happiness, it improved with *decreasing* speed for sadness (as in Sowden et al., 2021). Finally, we also identified that non-verbal reasoning ability was a significant predictor of emotion recognition accuracy [$F(1,83) = 5.84$, $= .018$]: those higher in non-verbal reasoning ability had better emotion recognition.

Appendix 4.2 – Participants' ethnicities in Chapter 5

Table A4.1.

Participants' ethnicities.

Racial Group	Ethnic Group	N	%
White	White English/ Welsh/ Scottish/ Norther Irish/ British	45	50.0%
	White European	6	6.7%
	White Irish	3	3.3%
	White Portuguese	2	2.2%
	White Greek	2	2.2%
	White Turkish	2	2.2%
	White Polish	2	2.2%
	White Caucasian	2	2.2%
	White Slavonic	1	1.1%
	White American	1	1.1%
	White Dutch	1	1.1%
	White Hungarian	1	1.1%
	White South African	1	1.1%
	White Ukrainian	1	1.1%
	White Australian	1	1.1%
	White New Zealand	1	1.1%
	White Honduran	1	1.1%
	White Scandinavian	1	1.1%
	Mixed/Multiple ethnic groups: White Lithuanian/Finish/Irish	1	1.1%
	Mixed/Multiple ethnic groups: White British and Irish	1	1.1%
	Mixed/Multiple ethnic groups: White regions	1	1.1%
	Mixed/Multiple ethnic groups: White Sardinian, Italian, Ashkenazi	1	1.1%
Asian	Asian Indian	2	2.2%
	Chinese	1	1.1%
Black	Black African	2	2.2%
	Black Afrikaans	1	1.1%
	Black British	1	1.1%
	Black South African	1	1.1%
Latino/Latina/Latinx	Latino	1	1.1%
Mixed/Multiple ethnic groups	Mixed/Multiple ethnic groups: White and Asian	1	1.1%
	Mixed/Multiple ethnic groups: White and Native American	1	1.1%
	Mixed/Multiple ethnic groups: White, Black Caribbean and Hispanic	1	1.1%

Appendix 4.3 – Participants' level of education in Chapter 5.

Table A4.2.

Participants' levels of education.

Highest level of education	N	%
Secondary School	10	11.1%
Sixth Form or College	19	21.1%
Diploma or equivalent level	8	8.9%
Undergraduate degree or equivalent level	27	30.0%
Master's degree or equivalent level	24	26.7%
PhD or equivalent level	2	2.2%

Appendix 4.4 – Explanation for why we calculated representational precision for each actor independently and then averaged across.

There is evidence that individuals have identity-dependent (i.e., actor-specific) visual representations of emotion (see [585,585]). This idea is logical: if you see someone with furrowed eyebrows, usually you would interpret them as angry, however, if you are aware that the actor *naturally* has angular eyebrows, you might not interpret them as such. Since individuals tend to build actor-specific expression representations, the most logical approach for calculating precision is based on one actor's expressions at a time, and then averaging across (rather than taking a standard deviation across every repetition of all four actor's expressions for each emotion).

If we were to take a standard deviation across all four actor's angry expressions, our results would be confounded by the extent to which participants have actor-specific representations. To illustrate this point, imagine that participant A has very precise visual representations of anger that tend to be actor-specific (in terms of speed). This participant may be likely to attribute 1.1 units of speed, 1.3 speed, 1.5 speed, and 1.7 speed to actor 1, and 3.5, 3.6, 3.8, and 3.9 to actor 2. It is reasonable for this participant to attribute different speeds to each actor, as there may be differences in the spatial configuration and speed of facial features between actors, and these cues heavily influence emotion judgements (see [239,519]). To give an example, it may be that actor 1 naturally has a more furrowed brow, meaning that they appear angry at lower speeds than actor 2. Based on their speed attributions, we can see that participant A has highly precise visual representations for each actor, but the speed of the representations differs between actors. In comparison, consider participant B that has imprecise visual representations of facial expressions, that are not individualised across actors. This individual may attribute 1.5 speed, 1.9 speed, 2.3 speed and 3.8 speed to actor 1, and 1.3 speed, 2.1 speed, 3.0 speed and 4.1 speed to actor 2 (and thus is imprecise across both actors). If we were to take a standard deviation across actors (as suggested by the reviewer as a potential alternative method), participant A would score -1.25, indicating low precision, and participant B would score -1.04, indicating higher precision. Hence, participant B who has considerably less precise visual representations would score higher than participant A in precision. However, using our method for calculating precision, participant A scores -0.22, indicating high precision, and participant B scores -1.12, indicating low precision. Hence, our method is a more valid way of measuring the precision of visual emotion representations.

Appendix 5

Supplementary Materials for Chapter 6

Similarities and differences in the psychological mechanisms involved in autistic and non-autistic emotion recognition

Connor T. Keating, Carmen Kraaijkamp, and Jennifer L. Cook

(Published in *PsyArXiv,* under review)

Reference: Keating CT, Kraaijkamp C, Cook J. Similarities and differences in the psychological mechanisms involved in autistic and non-autistic emotion recognition.
https://doi.org/10.31234/osf.io/6deqs

Appendix 5.1 – Participants' ethnicities in Chapter 6.

Table A5.1.

Participants' self-reported ethnicities.

Ethnicity	**N**
Asian Bangladeshi	1
Asian British	4
Asian Indian	2
Asian Iranian	1
Asian Sri Lankan	1
Black African	3
Black and Indian African	1
Black British	1
South East Asian	1
Turkish	1
White American	1
White and Asian	1
White and Black Caribbean	1
White and Native South American	1
White Eastern/Southern European	1
White English/Welsh/Scottish/Northern Irish/British	64
White European	1
White French	1
White Greek Cypriot	1
White Hungarian	1
White Irish	3
White Jewish	1
White Latino	1
White Other	1
White Sardinian, Ashkenazi and Italian	1
White Slavic	2
White South African	1
White Ukrainian	1
Total	**100**

Appendix 6

Supplementary Materials for Chapter 7

Comparing the spatiotemporal and kinematic properties of autistic and non-autistic facial expressions

Connor T. Keating, Sophie Sowden, and Jennifer L. Cook

(Published in *PsyArxiv,* under review)

Reference: Keating CT, Sowden, S, Cook J. Comparing the spatiotemporal and kinematic properties of autistic and non-autistic facial expressions.

Appendix 6.1 – Heatmaps of facial expressions

Access heatmaps of the average autistic, non-autistic, highly alexithymic and lowly alexithymic angry, happy and sad posed and spoken expressions at: https://osf.io/8a5yw/

Key
AP = Angry expressions in the posed condition
HP = Happy expressions in the posed condition
SP = Sad expressions in the posed condition
AS = Angry expressions in the spoken condition
HS = Happy expressions in the spoken condition
SS= Sad expressions in the spoken condition

Appendix 6.2 – Participants' ethnicity information in Chapter 7

Table A6.1.

Participants' ethnicity information.

Ethnicity	N
Asian British	2
Asian Indian	2
Asian Pakistani	1
Black African	1
Black British	1
Black Caribbean	2
White English/Welsh/Scottish/Northern Irish/British	40
White European	1
White Polish	1