A Transdiagnostic Approach to Emotion Recognition in Children: Behavioural and Neural Markers

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Thesis Summary

This thesis investigates how body context influences facial expression recognition in children with emotional, cognitive, and/or behavioural difficulties, and examines the neural markers supporting emotion recognition in these children. Recent research has suggested that facial expression recognition ability drives the influence of body posture on facial expression judgments, however it is unclear whether similar principles govern the integration of body context and facial expression in children with facial expression recognition difficulties. Additionally, it is unclear what common underlying structural and functional brain mechanisms are linked to emotion recognition abilities regardless of children's wider behavioural profile.

In Chapter 3, I demonstrated that typically developing children aged 4 to 10 years exhibit an association between proficiency in recognising isolated facial expressions and a bias towards body expressions in making facial expression judgments, parallel to prior studies. Chapter 4 extended this investigation to a transdiagnostic sub-clinical sample of children with emotional, cognitive, and/or behavioural difficulties, showing that they too, exhibit this pattern of integration despite their difficulties in recognising isolated facial expressions.

Chapter 5 explores the neural markers of emotion processing among these at-risk children, identifying a gray matter covariance network linked to facial expression recognition ability in regions such as the middle temporal gyrus, inferior frontal gyrus, and middle frontal gyrus, which are associated with social cognition and emotion processing. Chapter 6 examines brain activation synchrony in response to an emotional movie, finding that at-risk children with lower negative facial expression recognition abilities have higher synchrony in inferior

parietal and frontal regions, whereas those with higher abilities show greater synchrony in the ventromedial prefrontal cortex.

Overall, this thesis contributes to the understanding of facial and body expression integration among typically developing and at-risk children, and identifies potential neural markers linked to their emotion processing abilities that transcend diagnostic profiles. This thesis highlights the benefits of adopting transdiagnostic, dimensional approaches to improve our understanding of emotion recognition abilities.

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Acronyms

AAL Automated Anatomical Labeling.

ADHD Attention Deficit-Hyperactivity Disorder.

AFNI Analysis of Functional NeuroImages.

ANOVA Analysis of Variance.

ANTs Advanced Normalisation Tools.

BER Body Emotion Recognition.

BOLD Blood Oxygen Level Dependent.

CD Conduct Disorder.

COM Cerebromatic Toolbox.

CS Community Sample.

CSF Cerebrospinal Fluid.

CUBRIC Cardiff University Brain Research and Imaging Centre.

CUCHDS Cardiff University Centre for Human Developmental Science.

DARTEL Diffeomorphic Anatomical Registration Through Exponential Lie Algebra.

DMN Default Mode Network.

dmPFC Dorsomedial Prefrontal Cortex.

DSM Diagnostic and Statistical Manual of Mental Disorders.

DVARS Spatial Standard Deviation of Successive Difference Images.

EBA Extrastriate Body Area.

EPI Echo-planar Imaging.

FBA Fusiform Body Area.

FD Framewise Displacement.

FDR False Discovery Rate.

FER Facial Expression Recognition.

FFA Fusiform Face Area.

fMRI Functional Magnetic Resonance Imaging.

FSL FMRIB Software Library.

FWE Family Wise Error.

FWHM Full Width Half Maximum.

GM Gray Matter.

GMV Gray Matter Volume.

IC Independent Component.

ICA Independent Component Analysis.

ICASSO Independent Component Analysis for Clustering and Visualisation.

ICD International Classification for Diseases.

IFG Inferior Frontal Gyrus.

IPL Inferior Parietal Lobule.

Iq Quality Index.

IQR Image Quality Ratings.

ISC Inter-subject Correlation.

MDL Minimum Description Length.

MFG Middle Frontal Gyrus.

MNI Montreal Neurological Institute.

MP-RAGE Magnetization Prepared Rapid Gradient Echo.

MRI Magnetic Resonance Imaging.

MTG Middle Temporal Gyrus.

NDAU Neurodevelopmental Assessment Unit.

OFA Orbitofrontal Face Area.

PCC Posterior Cingulate Cortex.

PFC Prefrontal Cortex.

RDoC Research Domain Criteria.

ROI Region of Interest.

SDQ Strengths and Difficulties Questionnaire.

SoBM Source-based Morphometry.

STS Superior Temporal Sulcus.

SVC Small Volume Correction.

T1 The longitudinal relaxation time.

T2 The transverse relaxation time.

TD Typically Developing.

TIV Total Intracranial Volume.

TMS Transcranial Magnetic Stimulation.

ToM Theory of Mind.

TPJ Temporoparietal Junction.

TPM Tissue Probability Maps.

VBM Voxel-based Morphometry.

WM White Matter.

WPER Whole-person Emotion Recognition.

Acknowledgements

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Declaration

I hereby affirm that this thesis is the result of my own work. The information outlined in Chapter 4 was collected within the framework of a broader developmental study undertaken at CUCHDS. While the NDAU team facilitated the data collection for Chapter 4, I independently conducted all aspects of the work within the chapter, including its design, conceptualisation, and analysis.

Impact of Thesis

The chapters of this thesis presented at national and international conferences were listed below.

Chapter 4

Gezer Ö, Teufel C, van Goozen S, von dem Hagen E. Influence of context on facial emotion recognition in an at-risk sample of children with emotional difficulties. Platform Presentation. BACN. Annual Meeting of British Association for Cognitive Neuroscience, Cardiff, UK. September 2023.

Gezer Ö, Teufel C, van Goozen S, von dem Hagen E. Influence of context on facial expression perception in an at-risk sample of children with emotional difficulties. Poster. ECVP. European Conference on Visual Perception. Paphos, Cyprus. August 2023.

Chapter 5

Gezer Ö, van Goozen S, von dem Hagen E. Identifying Neural Markers of Facial Expression Recognition in a Neurodiverse Sample. Oral presentation. ESCAN. European Society for Cognitive and Affective Neuroscience, Ghent, Belgium. May 2024.

Chapter 1

General Introduction

1.1 Facial Expression Recognition

Identification of facial expressions is critical in the comprehension of emotions, particularly in early childhood when linguistic and cognitive abilities are still developing. Facial expressions serve as primary cues for children to understand the intentions, reasoning, and motivations behind expressed emotions (Parker et al. 2013; Ruba & Pollak 2020). As children's social cognition develops, they gradually learn to interpret and understand emotions through facial cues, a process crucial for their social and emotional development.

The ability to recognise facial expressions involves a range of cognitive and social abilities, including sensory maturity, attentional processes, memory, language, and knowledge of emotion labels (Erickson & Schulkin 2003; Frith 2009). Strengthening these cognitive and social abilities is essential for children's social and emotional growth, enabling them to interpret others' feelings through observing facial expressions, such as those of their parents or peers (Erickson & Schulkin 2003; Frith 2009).

In essence, the ability to identify facial expressions is foundational for children's socioemotional development. It equips them with essential skills for navigating social interactions, under-

standing others' emotions, and interpreting the complexities of social situations, ultimately facilitating their integration into society.

1.1.1 Development of Facial Expression Recognition

Facial expression recognition improves with age, and the sequence and trajectory of the recognition of emotional categories are characterised by distinct patterns throughout a child's development (Dalrymple et al. 2017; Rodger et al. 2015; Widen & Russell 2008). Due to infants' limited visual acuity and limits to other aspects of basic visual processing, there is little evidence to suggest that infants can discriminate facial expressions from birth. From 5-7 months, however, studies suggest that infants can recognise facial expressions across identities or intensity levels, based on habituation paradigms, and show a preference for smiling faces (Bayet & Nelson 2019; Bornstein & Arterberry 2003; C. A. Nelson et al. 1979; Safar & Moulson 2017; Widen 2013).

During early childhood, around the ages of 4 to 6, children initially categorise facial expressions based on valence, discerning positive from negative emotions. Happiness is the easiest facial expression to identify in matching and labelling tasks starting from early childhood (Barisnikov et al. 2021; Herba & Phillips 2004; Lawrence et al. 2015). This is followed by accurate identification of angry and sad facial expressions from the ages of 6 to 7 (Lawrence et al. 2015; Widen 2013). By middle childhood, children can distinguish fearful, disgusted, and surprised facial expressions, with the capacity to discern facial emotions depending on arousal and other physical cues developing later (Herba & Phillips 2004; Lawrence et al. 2015; Watling & Damaskinou 2018; Widen 2013).

Moreover, distinct facial expression categories exhibit different developmental trajectories. For instance, Rodger, Vizioli, Ouyang, & Caldara (2015) demonstrated that anger shows a gradual improvement through development until adulthood, while sadness remains stable from the age of 6. The developmental sequence and trajectory of emotion categories highlight the importance of examining different facial expression categories to gain insight into deviations

from typical socioemotional processing.

To sum up, research suggests that facial expression recognition begins early in development, with younger children demonstrating the ability to detect changes in facial expressions. As children grow, they develop the capacity to recognise facial expressions in a manner similar to adults, with distinct developmental pathways and trajectories for different emotion categories. Understanding the development of facial expression recognition is crucial for comprehending socioemotional processing and addressing potential challenges in this realm.

1.2 Facial Expression Recognition in Neurodiversity

A large body of research underscores that difficulties in recognising facial expressions are prevalent among individuals with various neurodevelopmental conditions, such as autism, Attention Deficit-Hyperactivity Disorder (ADHD), and Conduct Disorder (CD) (Collin et al. 2013; Peterson et al. 2015; Stagg et al. 2021).

Autism encompasses difficulties in social skills, including communication, interactions, and engaging in restricted, repetitive behaviours, interests, or activities (American Psychiatric Association 2013). Recent findings suggest a worldwide median prevalence of 65/10,000 for autism (Zeidan et al. 2022), prompting extensive investigation into facial expression recognition among individuals with autism (Lievore et al. 2023; Lord et al. 2020). Despite variations in research methodologies, studies often demonstrate that autistic children struggle to discern others' emotions based on facial cues in comparison to neurotypical peers (Chaidi et al. 2020; Shanok et al. 2019; Stagg et al. 2021; Wieckowski et al. 2020). In addition to behavioural studies, neuroimaging techniques like Functional Magnetic Resonance Imaging (fMRI) suggest that individuals with autism exhibit distinct brain activity patterns in response to facial emotions compared to their neurotypical peers (McKechanie et al. 2022; Vandewouw et al. 2020; A. T. Wang et al. 2004). In general, these findings underscore the significant challenge facial expression recognition poses for individuals with autism.

Attention deficit and hyperactivity disorder is characterised by inattention, hyperactivity, and impulsivity (American Psychiatric Association 2013), with growing evidence indicating difficulties in recognising subtle facial cues among individuals with ADHD (da Fonseca et al. 2009; Pelc et al. 2006; Yuill & Lyon 2007). A systematic review by Collin, Bindra, Raju, Gillberg, & Minnis (2013) revealed impaired facial emotion recognition among individuals with ADHD, suggesting a potential social-cognitive impairment. Moreover, studies have linked ADHD symptoms to reduced proficiency in recognizing facial expressions (Dede & White 2023). Neuroimaging studies have further elucidated differences in brain activity patterns when viewing facial expressions in individuals with ADHD compared to their neurotypical peers (Dan 2020; Ichikawa et al. 2014; Viering et al. 2022). Collectively, this body of research supports the notion that facial expression recognition difficulties are pervasive among individuals with ADHD.

Conduct disorder is a neurodevelopmental condition, characterised by persistent pattern of antisocial behaviours such as violating others' rights, physical aggression towards people and animals (Fairchild et al. 2019). CD is also distinguished by difficulties in the perception of facial expressions. Children with CD often exhibit challenges in emotion recognition tasks, particularly when it comes to negative emotions like fear and sadness (Blair et al. 2018; Fairchild et al. 2013; Martin-Key et al. 2021). For example, Martin-Key, Graf, Adams, & Fairchild (2021) demonstrated that children with CD exhibit poorer performance in recognising facial expressions compared to typically developing children, across both static and dynamic presentations. Similarly, Pauli et al. (2021) observed that children and adolescents with CD and elevated levels of callous-unemotional traits demonstrate significantly lower accuracy in recognising facial expressions than their neurotypical peers, particularly struggling with recognising fearful and sad facial expressions.

Recent meta-analyses and reviews support the notion that difficulties in facial expression recognition are common across neurodiverse populations (Blair et al. 2018; Collin et al. 2013; Lievore et al. 2023; Yeung 2022). This suggests that it may be beneficial to study

facial expression recognition as a dimensional characteristic, which transcends diagnostic categories. By focusing on facial expression recognition as a shared behavioural characteristic across various neurodiverse conditions, rather than specific diagnostic categories, it should be possible to gain a deeper understanding of potential underlying mechanisms. This approach not only highlights the importance of identifying shared features across various conditions but also helps us comprehend the fundamental difficulties neurodiverse children face in recognising facial expressions. Addressing these difficulties is crucial for gaining insight into how neurodiverse populations process social cues and how this influences their social and emotional well-being within the context of neurodiversity.

1.3 Facial Expression Recognition in Context

Traditionally, facial expression recognition studies have primarily focused on the recognition of isolated facial expressions. However, there has been a growing awareness that contextual cues, including body posture, background, and voice, influence the perception of facial expressions (Aviezer et al. 2012; de Gelder et al. 2006). Despite a growing body of research studying the influence of contextual cues such as body posture, on facial expression perception (Farley 2021), there remains a notable gap in understanding the interplay between facial expressions and body posture across neurodiverse populations (Mondloch 2012; Mondloch, Nelson, & Horner 2013).

While facial expressions have historically been central to investigations in emotion research, it is increasingly recognised that facial expression perception rarely operates in isolation from contextual cues (de Gelder et al. 2015). Notably, the body emerges as a primary source of contextual information in this regard, as faces are rarely seen without a body. Some examples of body expressions and their integration with facial expressions from the literature were shown in Figure 1.1. Recent research has highlighted the significant influence of body expressions on facial expression recognition abilities (Karaaslan et al. 2020; Wieser

& Brosch 2012). Studies have shown that congruent contextual cues e.g., body expressions can enhance our ability to recognize facial expressions relative to incongruent contextual cues (Kret et al. 2013; Theurel et al. 2016). When facial and bodily expressions align, they reinforce each other, making it easier for us to accurately interpret the emotional state being conveyed. Conversely, incongruent body expressions can interfere with our perception of facial expressions. Mondloch (2012) found that adults and children alike exhibit diminished accuracy in recognising facial expressions when they are accompanied by conflicting bodily cues. For instance, the perception of a sad facial expression may be impaired when paired with a fearful body expression, compared to a congruent pairing of a sad facial expression and a sad body expression (Aviezer et al. 2012; Mondloch 2012; N. L. Nelson & Mondloch 2017). However, importantly, the errors in facial expression categorisation are often biased towards the emotion conveyed by the body: Aviezer et al. 2008) found a bias toward the emotion expressed by the body when participants made judgments about the emotion of the face in the context of an incongruent body posture. For example, when participants were shown facial expressions of disgust paired with angry body posture, they often categorised the facial expression as angry. These findings underscore the significant influence that body expressions can have on our ability to recognise facial expressions.

The theoretical foundations of this body bias in facial expression recognition involve distinct contributions from multisensory integration, and attentional mechanisms. Together, these elements influence how facial expressions are interpreted and recognised in the presence of bodily cues. Multisensory integration refers to the fact that faces are usually accompanied by a diverse range of visual, auditory, olfactory, and somatosensory stimuli. When both facial and body expressions are present, these multiple cues help clarify ambiguous facial emotions, resulting in greater accuracy in emotion recognition to the extent of the ability to recognise facial expressions accurately. This implies that body expressions could significantly influence how facial expressions are interpreted if there is not enough competency in recognising facial expressions (de Gelder 2009). Another explanation is attentional mechanisms where body

expressions can direct or influence where attention is allocated, particularly causing distracted attention when body and facial expressions are incongruent. While humans generally prioritise faces over broader scenes, adults have been found to also focus on dynamic body movements over faces, indicating that body cues have capability to significantly influence their attention (O'Toole et al. 2011; Stoesz & Jakobson 2014). Therefore, this shift in attention might lead to inaccurate identification of facial expressions and bias towards body emotion.

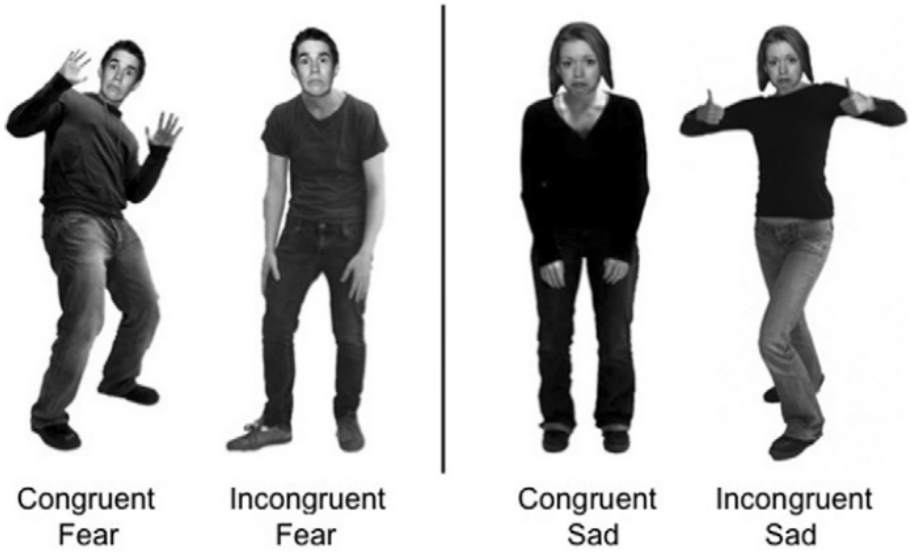

Figure 1.1: Body expressions from the literature from Mondloch, Horner & Mian, 2013.

1.3.1 Facial Expression Recognition in Context in Developmental Populations

While the influence of body context on facial expressions has received attention in adult populations, there remains a scarcity of research on this topic in children. Notable studies by Mondloch (2012) and Mondloch, Nelson, & Horner (2013) investigated congruency effects in young children and adults by presenting sad and fearful facial expressions alongside congruent and incongruent body postures. The participants were instructed to focus solely on facial expressions in making their judgments. They discovered that children, as young as 6 years old, exhibit lower accuracy in facial expression recognition for incongruent face

and body posture pairs compared to congruent pairs, a trend mirroring finding observed in adults, where performance was similarly influenced by incongruent body postures. However, children were more influenced by the incongruent posture (i.e. made more errors) than adults, underscoring the potential impact of age on contextual influences. These findings underscore the importance of further research into how bodily cues influence the recognition of facial expression across different developmental stages, revealing age-related differences in the impact of contextual influences.

While Mondloch and colleagues have made significant contributions to understanding the influence of body context on facial expression recognition, recent research, Ward et al. (2023), has studied whether children exhibit a bias toward the body emotion in interpreting facial expressions (i.e. whether they are biased towards the body emotion in judging the facial expression), and the underlying mechanisms driving this bias. Their research demonstrated age-related differences in facial expression recognition and the influence of contextual cues. They found that facial expression recognition abilities of children improve with age, while the biasing influence of body expressions on facial expression recognition decreases with age. This provides some support for the notion that there may be a link between isolated facial expression recognition ability and the biasing influence of body posture on facial expression recognition. This association points to a potential mechanism underpinning the influence of body context on facial expression perception, whereby individuals with facial expression recognition difficulties may rely more heavily on contextual information from the body to interpret facial expression.

1.4 Facial Expression Recognition in Context within Neurodiversity

While studies focusing on adults and children have revealed intriguing findings regarding the interplay between body expressions and facial cues, relatively few investigations have

explored this phenomenon in populations with neurodevelopmental conditions. This gap in research highlights the need to examine the influence of body context on facial expression recognition in individuals with difficulties in facial expression recognition.

In a recent study focusing on adults with autism, Brewer, Biotti, Bird, & Cook (2017) found that both autistic and non-autistic adults were similarly influenced by emotional cues from body expressions when making judgments about facial expressions. They found no differences in discrimination sensitivity for isolated facial expressions between autistic and non-autistic individuals but found that there was a negative association between the biasing influence of body context and isolated facial expression discrimination ability in the autistic group. This might indicate that in adults with autism, similar mechanisms may underlie the influence of body context on facial expression perception, as observed in typical development (Ward et al. 2023).

As discussed in earlier sections, individuals with ADHD often face difficulties in recognising facial expressions (Dede & White 2023; Yuill & Lyon 2007). While there is limited research specifically examining the impact of body context on facial expression recognition in ADHD, some studies have explored how these individuals recognise body expressions and integrate them with facial cues. For instance, Thoma et al. (2020) found that individuals with ADHD had difficulty recognising body expressions, although they were capable of identifying facial expressions. The study also revealed brain activity changes related to emotional valence and the configurational processing of both facial and body expressions. Additionally, da Fonseca et al. (2009) investigated emotion understanding in children with ADHD using contextual cues, including body expressions alongside facial expressions. They discovered that children with ADHD struggled not only with isolated facial expressions but also with those that included contextual cues. These studies indicate that individuals with ADHD employ different mechanisms when integrating contextual information with facial expressions during emotion processing, yet they do not provide a direct link to how body expressions specifically influence facial expression recognition.

A limited number of studies have investigated the influence of body context on facial expression recognition in adolescent offenders. Pino et al. (2019) explored the effects of contextual body cues on facial expression recognition in adolescent males, both those involved in criminal activities and those who were not. They observed that adolescents engaged in criminal activities faced greater challenges in recognising facial expressions compared to non-offender adolescents, especially when facial and body expressions conveyed conflicting emotions. Similarly, Santamaría-García et al. (2019) examined the influence of body context in adolescent offenders compared to a non-offender group. They found that body context significantly influenced facial expression recognition accuracy when the emotional expressions of the face and body were incongruent. Notably, adolescent offenders exhibited a heightened reliance on body cues, leading them to categorise facial expressions based on the emotions displayed by body expressions during incongruent trials.

Considering how multisensory integration and attentional mechanisms might operate differently in children with neurodevelopmental conditions, it is important to referring the altered sensory processing and attentional biases in conditions such as autism, ADHD, and CD. Their differences in these cognitive abilities might cause them paying more attention to a specific type of stimuli leading them to inaccurately recognise facial expressions, led by emotion conveyed in body expressions. Especially when they lack the ability to accurately identify facial expressions, they might end up showing lower performance compared to their neurotypical peers. For instance, autistic individuals tend to focus on mouth more than eyes on the face (Bar-Haim et al. 2006) and they present broader difficulties in identifying emotions from faces, bodies, and voices (Lott-Sandkamp et al. 2023; Philip et al. 2010). The altered ability to integrate multisensory information, coupled with atypical attention allocation, could lead to a greater body bias, impacting the accuracy of their facial expression recognition.

In conclusion, research into the influence of body context on facial expression recognition reveals that individuals with neurodevelopmental conditions, such as adults with autism

and adolescent offenders, exhibit heightened susceptibility to contextual cues, e.g., body expressions, compared to their neurotypical peers. While most studies did not look into mechanisms that might drive the influence of body context, Brewer, Biotti, Bird, & Cook (2017) results in autistic adults are broadly consistent with findings from Ward et al. (2023), where individuals with poorer facial expression recognition abilities rely more on body context in making their judgements of facial expression. However, it is unclear to what extent this would generalise to other individuals and/or groups with difficulties in facial expression recognition. This highlights the importance of exploring transdiagnostic approaches, as they can contribute to a more expansive understanding of emotion recognition across diverse conditions and help identify shared characteristics and mechanisms.

1.5 Face Perception and Facial Expression Processing in the Brain

Faces convey multifaceted information for social interaction, including identity, emotion, gender, and focus of attention. Face perception engages complex and distributed neural networks across the brain. The organisation of face perception in the brain encompasses not only visual regions, but also extends to other specialised regions to process the identity and emotion of faces (Haxby et al. 2000; Haxby & Gobbini 2011).

Functional neuroimaging studies highlight a strong connection between face perception and occipitotemporal regions, namely the Fusiform Face Area (FFA), Superior Temporal Sulcus (STS), Orbitofrontal Face Area (OFA), as a "Core System" for face perception. The FFA is predominantly involved in encoding facial identity (M. Liu et al. 2021; Tsantani et al. 2019; Tsantani et al. 2021; P. Xu et al. 2021), while the STS shows enhanced brain activity in response to facial features and movements (M. Liu et al. 2021; Schobert et al. 2018). Perception of faces and face parts (e.g., eyes, mouth, nose), differentiating familiar faces from unfamiliar were found to exhibit heightened brain activity in the OFA (Eick et al. 2021;

J. Liu et al. 2010; Thome et al. 2022; J. Zhang et al. 2022).

Beyond these core regions, an extended network processes higher-order information from faces, such as emotion, personal identity, and speech, involving the amygdala, insula, anterior temporal lobe, auditory cortex (Bayet & Nelson 2019; P. Xu et al. 2021). For instance, meta-analyses by V. I. Müller, Höhner, & Eickhoff (2018) and P. Xu, Peng, jia Luo, & Gong (2021) reveal distinct neural activations for emotional versus neutral faces, implicating regions including the fusiform gyrus, amygdala, and temporal areas. M. Liu, Liu, Zheng, Zhao, & Fu (2021) further emphasise the differential activation in response to dynamic versus static facial expressions across regions like fusiform gyrus, middle temporal gyrus, amygdala, middle occipital gyrus, and STS. Figure 1.2 illustrates the organisation of the "Core System" and "Extended System" as discussed, depicting the neural networks involved in face perception modified from Haxby, Hoffman, & Gobbini (2000).

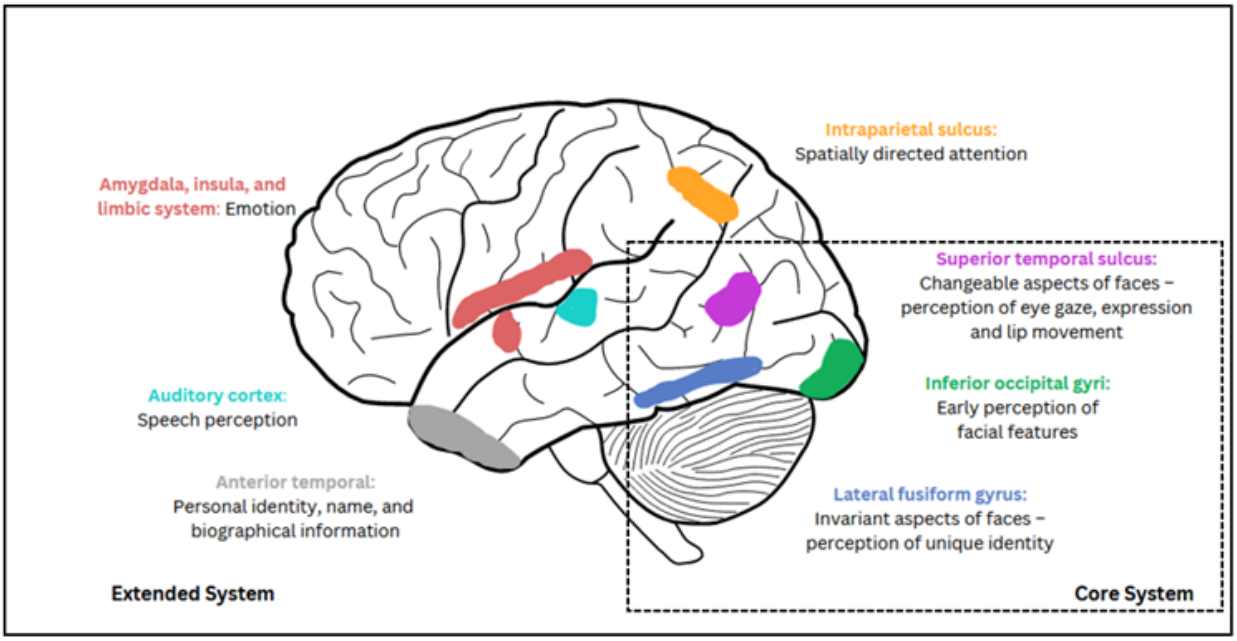

Figure 1.2: Haxby model of the human brain for face perception.
Modified from Haxby et al., 2000.

In summary, research supports pivotal roles of the FFA, STS and OFA in face perception, alongside a broader network in processing facial features of emotion and movements. Synthesising insights from these studies reveals a dynamic interplay among various brain

regions, elucidating their unique contributions to the processing of facial expressions and the integration of emotional and cognitive dimensions in social interaction.

1.6 Face Perception and Facial Expression Recognition in the Brain among Neurodiverse Populations

Neuroimaging techniques have played a crucial role in elucidating the underlying neural correlates of various neurodevelopmental conditions such as autism, ADHD, and CD. The most commonly employed methods in this field are Voxel-based Morphometry (VBM) and Source-based Morphometry (SoBM), which offer complementary insights into structural brain variations associated with these neurodevelopmental conditions. By providing valuable information on the regional differences in brain volume and structural patterns, they highlight markers of atypical development in key areas involved in cognition, emotion, and behaviour. By examining these structural variations, we can better understand how neurodevelopmental conditions manifest at the neural level, paving the way for a deeper understanding of these conditions.

Autism has been one of the most studied neurodevelopmental conditions that Gray Matter Volume (GMV) differences from their neurotypical peers were demonstrated in various studies. For example, Uono et al. (2022) investigated how difficulties in recognising facial expressions are associated with changes in gray matter volume. They found no correlation between facial expression recognition accuracy and gray matter volume in individuals with autism, whereas neurotypical peers displayed a positive correlation between facial expression recognition and gray matter volume in the right inferior frontal gyrus. Yang et al. 2016 ran a voxel-wise meta-analysis on individuals with autism, including over 300 individuals with autism, and they found that autistic individuals have significantly heightened levels of GMV in the middle temporal gyrus, superior temporal gyrus, postcentral gyrus and parahippocampal gyrus whereas they had diminished GMV in the anterior cingulate cortex and cerebellum. In a more

recent meta-analysis, researchers reviewed VBM studies on autism in the last twenty five years to detect a structural variation pattern of autism. They found that autistic individuals had less GMV in the cerebellum, and more in the parietal ,temporal and frontal brain regions. (Liloia et al. 2024). In a follow-up to their previous analysis of the Longitudinal European Autism Project data, Mei et al. 2024 conducted a VBM comparison study, identifying two independent components associated with autism. The first component showed larger volumes in regions such as the bilateral insula, inferior frontal gyrus, orbitofrontal cortex, and caudate in individuals with autism compared to controls. The second component was linked to increased volumes in the bilateral amygdala, hippocampus, and parahippocampal gyrus in the autism group. These findings underscore distinct patterns of GMV in autistic individuals and highlight the importance of examining gray matter covariations to better understand neural markers of autism. The study's replication using the ENIGMA cohort further reinforces the reliability of these GMV differences between autistic and non-autistic individuals. By applying SoBM on autism, Grecucci et al. 2016 and Pappaianni et al. 2018 identified gray matter covariation patterns where they found a distinct gray matter network involving the frontal and temporal regions such as inferior–middle–superior frontal gyrus, the inferior–middle–superior temporal gyrus, the fusiform gyrus. Functional studies have linked facial identity and facial expression recognition in autism to atypical functioning of fusiform gyrus, amygdala, and occipital areas (Joseph et al. 2015; McKechanie et al. 2022; Y. Wang et al. 2024). A review by Nomi & Uddin (2015) found that brain activation patterns in autistic individuals in response to facial expressions depend on task demands, where passive viewing of emotional faces did not lead to changes in activation patterns relative to non-autistics, but orthogonal tasks (gender, identity) did. For example, gender identification of facial expressions led to reduced activation of fusiform gyrus, and increased activation in STS and amygdala (Critchley et al. 2000). In a recent meta-analysis of whole-brain fMRI studies has provided compelling evidence that diminished amygdala activation is a key difference between autistic individuals and neurotypical controls during face processing tasks. This finding supports the growing body of research on the extended face perception system in

autism. The study also highlights that amygdala impairment is a central factor contributing to social deficits and facial recognition impairments in autistic individuals (Costa et al. 2021). However, some research has not found any difference in amygdala activation in response to facial expressions in autistic individuals (Langenbach et al. 2024) which suggests research on facial expression processing in the brain in autism is mixed and highly dependent on task demands.

The variations in the GMV was observed in various regions among populations with ADHD. Y. Zhao et al. 2020 found that individuals with ADHD have diminished GMV in the frontal regions and cingulum compared to their neurotypical control group. A recent meta-analysis demonstrated that the precentral gyrus and frontal regions have less GMV in ADHD groups compared tot he neurotypical peers, supporting the previous findings in the literature and linking these regions to the action and emotion related functions (Long et al. 2022). Another study on structural variations in ADHD used SoBM to detect gray matter covariation components, including over 250 indiviudals with ADHD and a comparable size of a control group. They found one Independent Component (IC) associated with ADHD, including the occipital areas, frontal areas, pre- and post-central gyrus, and precuneus, by showing the beneficial use of a multivariate analysis (Bralten et al. 2017). Viering et al. (2022) found that adolescents and young adults with ADHD had slower responses and made more errors in an emotional-face matching task, with decreased activity in face-related areas such as the amygdala, hippocampus, occipital regions, and fusiform gyrus. Likewise, Zuberer et al. (2022) showed that adults with ADHD have lower levels of activation in the superior temporal gyrus linked to facial expression recognition performance compared to neurotypicals. Similar to populations with autism and ADHD, individuals with conduct disorder also exhibit reduced activation in the amygdala and temporal regions, overlapping with face-selective areas, when viewing fearful facial expressions and empathic pain images (Berluti et al. 2023). Vandewouw et al. (2020) conducted an fMRI study to examine facial emotion processing among children with autism, ADHD, and obsessive-compulsive disorder, and neurotypical children. They

found that children with neurodevelopmental conditions responded similarly to emotional faces compared to typically developing children, implying some shared neural mechanisms in response to emotional faces. These investigations underscore the intricate relationship between neural mechanisms and facial expression processing across various neurodevelopmental disorders. They highlight that neural mechanisms of facial emotion processing may manifest in various regions, including overlapping regions across neurodevelopmental conditions, reflecting common neural markers associated with difficulties in facial expression processing.

CD has been another most commonly studied neurodevelopmental condition conducting structural analysis. A recent investigation using ENIGMA dataset, researchers identified reduced GMV in many regions, especially in the amygdala, caudate, and hippocampus among individuals with CD compared to neurotypical peers. The most prevalent structural variations were regions associated with emotion processing, regulation and empathy (Y. Gao et al. 2024). Tully et al. 2023 and colleagues ran a systematic review and meta-analysis on disruptive behaviours, antisocial behaviours which are likely to be observed within CD, to identify common structural differences among this sample. They found significant decreases in the total GMV and the amygdala among individuals with antisocial groups compared to the controls. Despite there is no SoBM study focused on CD to my knowledge, Harenski et al. 2020 studied the criminal offenders with and without suicidal attempts. They found a gray matter covariation network including the posterior cingulate, dorsal prefrontal cortex, and amygdala with reduced GMV. However, it is important to note that this study does not focus on disruptive behaviours or conduct problems even it shows some relevant findings related to structural brain differences.

In conclusion, structural imaging analyses, particularly VBM and SoBM, and fucntional studies have significantly advanced our understanding of brain variations in neurodevelopmental conditions such as autism, ADHD, and CD. Research investigating the neural mechanisms behind variations in facial expression recognition within specific disorders, such as autism, ADHD, CD, highlights the necessity of examining neural markers across neurodevelopmental

conditions. These findings, which stem from studying the disorder-specific neural bases, suggest that a transdiagnostic approach could be more effective. Instead of focusing on disorder-specific approaches, exploring facial expression recognition abilities and associated neural mechanisms across a broad range of facial expression recognition abilities, encompassing children with emotional, cognitive, and/or behavioural difficulties as well as neurotypical children, could identify common neural mechanisms or patterns that transcend diagnostic boundaries. This transdiagnostic approach may shed light on the dimensional nature of facial expression recognition abilities and underlying neural mechanisms, rather than treating them as categorical deficits specific to certain disorders.

1.7 Further Explorations on Emotional Understanding in Neurodiversity

In this section, I mentioned the common and distinctive features of neurodevelopmental conditions within genetics, phenotyping, Theory of Mind (ToM), and differentiation and models on emotional representation and dysregulation.

1.7.1 Genetics and Phenotyping on Neurodiversity

Understanding how neurodevelopmental conditions such as autism, ADHD, CD are characterised at behavioural, neurobiological, and genetic levels is crucial. This multilevel perspective helps highlight the shared and unique aspects of these conditions, contributing to a more nuanced understanding. Previously, I reviewed the behavioural and neurobiological literature on these conditions, using the Research Domain Criteria (RDoC) framework to investigate facial expression processing across different levels. Here, I briefly discuss the broader phenotypic and genetic considerations for these neurodevelopmental conditions.

Neurodevelopmental conditions like autism, ADHD, CD are highly heterogeneous and can co-occur, suggesting overlapping neurobiological and behavioural characteristics (Hanly et al.

2021). Autism and ADHD in particular, are known to be highly heritable, with multiple genes contributing to each condition rather than a single genetic determinant. These shared genetic factors suggest complex interactions that impact cognitive, social, and emotional domains, albeit with varying levels of impairment (Morris-Rosendahl & Crocq 2020). In contrast, CD focuses primarily on antisocial behaviours, such as aggression and externalising problems. These characteristics are linked to differences in emotion processing, reward and punishment sensitivity, and empathy across behavioural and neuroimaging studies (Fairchild et al. 2019). CD's heritability is moderate, with gene-environment interactions playing a significant role (Gelhorn et al. 2005; Salvatore & Dick 2018). Evidence from a comprehensive twin study indicates that genetic influences on CD behaviours, such as lying, fighting, and aggression, are moderate, with environmental factors also contributing significantly to variability (Gelhorn et al. 2005).

In summary, by exploring these neurodevelopmental conditions from multiple levels of analysis, including behavioural, neurobiological, and genetic factors—we gain insights into both their shared and distinct features. This comprehensive understanding can inform on the underlying mechanisms and the development of neurodevelopmental conditions.

1.7.2 Theory of Mind

ToM refers to the cognitive ability to understand that others have beliefs, desires, intentions, and perspectives that are different from one's own. This ability is crucial for social interactions and communication (Fu et al. 2023). ToM is a multifaceted concept including cognitive and affective features and been linked with cognitive, social, and emotional processing through development (Meinhardt-Injac et al. 2020). The ToM related tasks include identifying false beliefs, interpreting complex emotional cues, understanding intentions and beliefs, as well as tasks related to reading comprehension, language processing, and self-other differentiation (S. Gao et al. 2023). The network of ToM and other relevant networks, particularly Default Mode Network (DMN) and reinforcement network are shown in Figure 1.3 to enhance

understanding of the link between emotion processing and neurodevelopmental conditions.

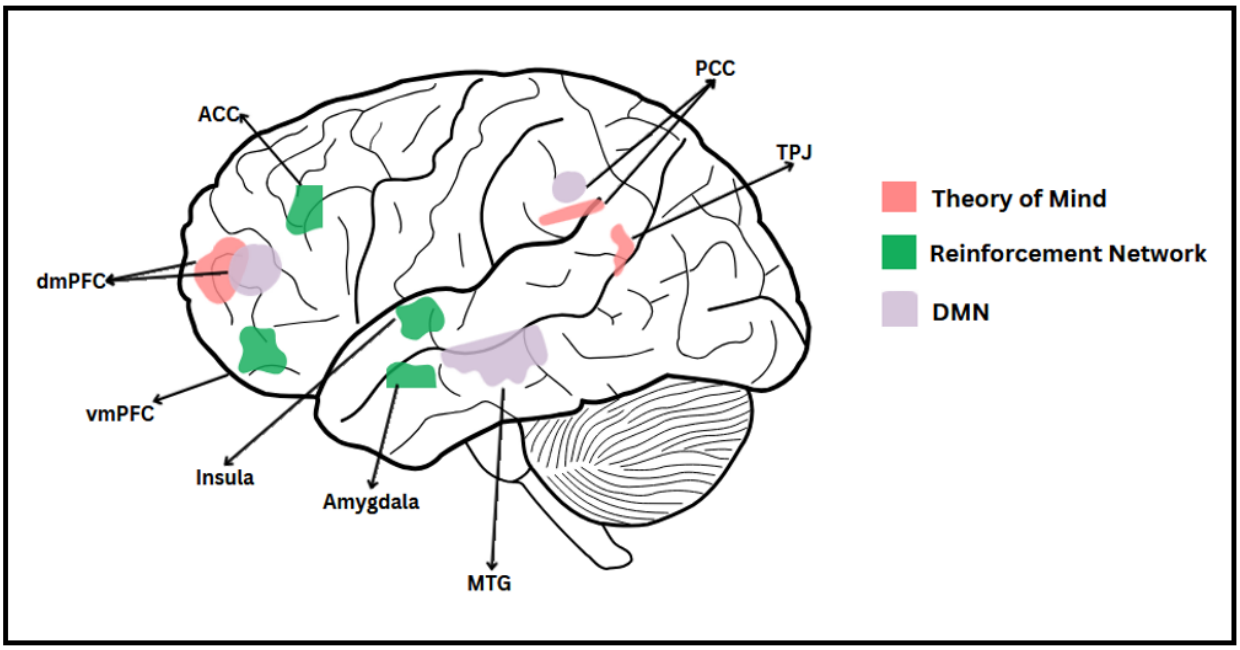

Figure 1.3: Brain Networks involved in emotion processing other than face perception. ACC: Anterior Cingulate Cortex; DMN: Default Mode Network; dmPFC: Dorsomedial prefrontal Cortex; MTG: Middle Temporal Gyrus; PCC: Posterior Cingulate Cortex; TPJ: Temporoparietal Junction; vmPFC: Ventromedial Prefrontal Cortex.

Both facial expression recognition and ToM are highly associated with healthy development and effective social interactions. Mier et al. (2010) found overlapping activation regions for both of these abilities, however they found higher activation for ToM in the Inferior Frontal Gyrus (IFG), superior temporal sulcus, temporal pole, and amygdala. Furthermore, Lee et al. (2014) showed the mediating role of ToM among facial emotion recognition and reasoning abilities. The link betweeen ToM and facial emotion recognition has been shown in neurodevelopmental conditions as well such as autism,

Research has investigated the link between ToM and different neurodevelopmental conditions, focusing on how ToM impairments may present in these conditions (Meinhardt-Injac et al. 2020; Duval et al. 2011; Tager-Flusberg & Sullivan 2000). Autism is notably characterized by difficulties in facial processing and social skills, as highlighted by behavioural and neuroimaging studies. Previous meta-analyses and reviews have indicated that individuals with autism

show reduced performance in ToM tasks, such as identifying false beliefs, interpreting complex emotional stimuli, understanding intentions, and self-other processing (S. Gao et al. 2023; Szamburska-Lewandowska et al. 2021). Imaging studies have reported decreased activity and differences in White Matter (WM) and Gray Matter (GM) metrics in ToM-related areas such as the Temporoparietal Junction (TPJ), Posterior Cingulate Cortex (PCC), and Dorsomedial Prefrontal Cortex (dmPFC) in individuals with autism (Rafiee et al. 2022; R. A. Müller & Fishman 2018).

Similarly, ADHD has been linked with reduced ToM abilities, which reflect their inattentiveness and social challenges (Szamburska-Lewandowska et al. 2021). ToM deficits have been linked to low inhibitory control, which is crucial for regulating cognitive and emotional processes in social contexts. This affects the ability to consider others' viewpoints and express emotions appropriately. Pineda-Alhucema et al. (2018) explored whether executive functioning difficulties contribute to ToM impairments in individuals with ADHD. Their review found mixed results due to the heterogeneous nature of the studies, though consistent ToM challenges were still observed. A recent meta-analysis by Nejati (2022) revealed that individuals with ADHD perform significantly worse than neurotypical peers on ToM tasks. Neuroimaging evidence further supports alterations in ToM-related areas, with individuals with ADHD displaying reduced GMV in the amygdala and hippocampus (Novak et al. 2024). Sutcubasi et al. (2020) reported that ADHD is linked with lower functional connectivity within the DMN and cognitive control networks, which encompass ToM regions such as the TPJ, PCC, and Prefrontal Cortex (PFC).

Finally, CD is associated with delays in ToM skills, particularly with elevated aggression and psychopathic traits being linked to ToM deficits (de la Higuera-González et al. 2024). Sharp (2008) found a positive correlation between conduct problems in children and impaired ToM abilities. This finding aligns with a recent review of aggression and ToM, which identified a significant negative relationship between ToM and aggression across children, adolescents, and adults (Ekerim-Akbulut et al. 2024). Psychopathic traits, which are often comorbid with

CD, particularly in their interpersonal and affective dimensions, have been found to be more strongly linked with ToM impairments. Furthermore, Fairchild et al. (2019) reviewed imaging studies on CD and found that individuals with CD exhibit reduced activity in brain regions involved in emotion processing, empathy, and reward learning, which overlap with regions critical for ToM.

In summary, ToM is an important developmental ability requiring both cognitive and social processing. The involvement of face perception and recognising facial expressions are noteworthy in the scope of this thesis. The exploration of ToM deficits across various neurodevelopmental conditions highlights the intricate relationship between cognitive processing and social functioning observed in behavioural and neurobiological levels.

1.7.3 Distinctions in Emotion Processing

Emotional dysregulation and emotional representations are two distinct constructs within the field of psychology and psychiatry. Emotional dysregulation refers to the inability to manage and respond to emotional experiences in a socially acceptable and flexible manner. In contrast, emotional representations pertain to the mental processes involved in the perception, interpretation, and memory of emotional experiences, particularly referring to the visual representations of emotions (D'Agostino et al. 2016; Paulus et al. 2021; Thompson 2019). Emotional dysregulation is a transdiagnostic feature observed across various mental disorders, including autism (Samson et al. 2014; McDonald et al. 2024), and CD (Mitchison et al. 2020; Fairchild et al. 2019; Cappadocia et al. 2009).

In their study, Keating et al. (2023) examined the differences in processing and identifying emotional representations between individuals with and without autism. They discovered that autistic individuals demonstrate greater precision in visual emotion representations compared to their non-autistic peers, particularly regarding speed. However, this increased precision does not translate to improved accuracy in emotion recognition tasks. This finding suggests that, while autistic individuals may process visual emotional cues more rapidly,

they struggle to utilise these representations for emotional understanding is not necessarily enhanced, possibly implying that they rely less on such emotional representations to guide their social processing. For non-autistic individuals, successful emotion recognition was influenced by non-verbal reasoning skills as well as the interaction between the precision of their emotional representations and their ability to match these representations effectively. In contrast, none of these factors significantly contributed to the emotion recognition abilities of autistic individuals, suggesting that they may employ a fundamentally different mechanism for recognising emotions. These observations align with the work of Lozier et al. (2014) and Jelili et al. (2021), which posits that neurodevelopmental processes and social experiences typically enhance general face-emotion recognition abilities as children develop. However, children with autism often experience disruptions in these processes, indicating a widespread functional impairment in the neural architecture responsible for face-emotion processing. Thus, the findings from both studies collectively underscore the complexities of emotion recognition in autistic individuals, suggesting that while they may possess certain strengths in visual precision, they also face significant challenges in effectively interpreting and recognising emotional expressions due to underlying neurodevelopmental differences.

Following on their work Keating & Cook (2023) introduced the 'Inside-Out Model' of emotional recognition, which provides a theoretical framework for understanding variability in emotional processing across individuals. According to this model, some individuals develop modular emotional "maps," where their visual and experiential emotional representations are distinct and consistent—meaning emotions like anger, happiness, and sadness are perceived as clearly different from one another. For other individuals, however, these representations are more fluid and overlapping, leading to greater difficulty in distinguishing between emotions like anger, happiness, and sadness, which may share similar experiential or perceptual qualities and thus are more easily confused. They revealed that individuals with modular emotional maps tend to have better emotion recognition abilities. Furthermore, the finding that autistic individuals exhibit precise yet less efficient emotional representations may imply that their

emotional maps are either more rigid or operate in a less integrated manner compared to non-autistic individuals. Autistic people may perceive emotions with high accuracy in terms of visual detail, yet their emotional experiences might not align as distinctly or consistently with these visual cues, resulting in less efficient use of these representations in social contexts. In other words, while autistic individuals may have highly detailed emotional representations, these representations may not be as meaningfully integrated into their broader emotional processing network, contributing to the observed challenges in emotion recognition. This divergence aligns with the concept of emotional representations that are less modular and more variable, as proposed in the 'Inside-Out Model,' which may be characteristic of the unique emotional processing mechanisms in autism.

This concept ties in with findings related to CD, such as those presented by Dawel et al. (2012). Their meta-analyses revealed widespread impairments in emotion recognition across multiple modalities (both facial and vocal) in individuals with psychopathic traits, including both adults and children/adolescents. Importantly, these impairments were not limited to fear and sadness but extended to a broader range of emotions, indicating pervasive deficits. These findings can be understood within the framework of the 'Inside-Out Model' by Keating & Cook (2023), which explains how emotional recognition depends on the consistency and distinctiveness of emotional maps. In individuals with CD or psychopathic traits, the emotional processing deficits could be indicative of an atypical mapping system, where emotional experiences and their corresponding representations are not well differentiated. The amygdala, a key structure involved in emotional processing, is believed to function atypically in individuals with psychopathy, which may contribute to less distinct emotional maps. Consequently, individuals with CD may exhibit emotional representations that overlap more frequently, leading to a blurring of boundaries between emotions like anger, fear, or sadness. This lack of modularity and clarity in emotional representations aligns with the idea of variable and overlapping experiences proposed in the 'Inside-Out Model,' thus contributing to the broad difficulties in emotional recognition observed in these populations.

1.8 Transdiagnostic Approach

Recently, there has been a notable shift in research towards transdiagnostic approaches, moving away from the traditional categorical approaches based on diagnostic manuals like the Diagnostic and Statistical Manual of Mental Disorders (DSM) (American Psychiatric Association 2013) and International Classification for Diseases (ICD) (WHO 2004). Transdiagnostic approaches prioritise understanding shared mechanisms underlying various neurodevelopmental conditions. Categorical approaches have been criticised for their failure to capture the full spectrum of psychopathology and overlap between conditions, resulting in challenges related to heterogeneity within neurodevelopmental conditions, the rigid criteria required for diagnosis, and the management of comorbidities (Fusar-Poli et al. 2019; Insel et al. 2010; Stanton et al. 2020). Transdiagnostic approaches benefit from a comprehensive examination that delves into specific behavioural characteristics. Through the capture and analysis of a spectrum of these traits, this approach allows for the identification of common underlying mechanisms associated with difficulties. Consequently, it has the potential to enable the implementation of tailored interventions and treatments that effectively target specific difficulties, regardless of diagnostic category or even in the absence of a diagnosis.

Recent evidence suggests that traits associated with specific diagnostic categories, such as difficulties in facial expression recognition, are common to several conditions, and do not adhere to strict categorical boundaries. Rather, research indicates that variations in these functional domains span a continuum, encompassing both individuals within and across diagnostic groups and those in the general population (da Silva Ferreira et al. 2014; Golan et al. 2015; Pelc et al. 2006). The RDoC is a framework developed by the National Institute of Mental Health to guide research on the underlying mechanisms of mental disorders (https://www.nimh.nih.gov/research/research-funded-by-nimh/rdoc, Insel et al. 2010). The framework prioritises studies on neurodevelopment and environmental influences, and their interactions, to understand the etiology of disorders throughout the lifespan (Cuthbert 2020). The RDoC approach aims to investigate various dimensions of cognitive and psychological

functioning, with the goal of enhancing our understanding of the underlying mechanisms of psychological processes and developing treatments and interventions focused on symptoms rather than specific diagnoses. The RDoC framework is structured around five main domains: Negative Valence Systems, Positive Valence Systems, Cognitive Systems, Systems for Social Processes, and Arousal/Regulatory Systems. Within each domain, multiple levels of analysis are considered, including genes, molecules, cells, circuits, physiology, behaviour, and self-report (Regier et al. 2013; Xia et al. 2018' Ramey & Regier 2019).

The RDoC framework transcends traditional diagnostic boundaries, recognising the shared characteristics across psychopathological presentations. In this thesis, the focus was on facial expression recognition functioning in a diverse sample, grounded in the RDoC approach. Facial expression recognition in the context of RDoC could be considered under Systems for Social Processes, as this domain covers understanding and interpreting social signals, including the recognition of facial expressions, which is crucial for social interaction. This approach enables an inclusive perspective, wherein individuals with varying levels of difficulties are included to elucidate the underlying mechanisms of facial expression recognition across a spectrum of abilities. Moreover, adopting such an approach directs attention towards dimensional constructs and neurobiological aspects, fostering a more nuanced understanding of the complex processes underlying emotion recognition skills in both typically developing and at-risk children.

It is important to clarify how I have employed this terminology throughout my thesis. As mentioned earlier, the transdiagnostic approach focuses on identifying common underlying mechanisms across various mental disorders rather than adhering to specific diagnostic categories. This approach aims to address the limitations of traditional categorical methods in psychology and psychiatry (Sauer-Zavala et al. 2017). As noted by Sauer-Zavala et al. (2017) and Fusar-Poli et al. (2019), transdiagnosis facilitates a more nuanced understanding of psychological phenomena, enabling researchers and clinicians to identify shared mechanisms across diverse disorders. However, the term "transdiagnostic" is used inconsistently in the

literature, lacking clear definitions that promote a common understanding across studies (Sauer-Zavala et al. 2017; Parnas et al. 2019).

Given this variability, it is essential for my research to clarify how I define and use the terms "transdiagnostic" and "neurodiverse." In this thesis, "transdiagnostic" refers to my focus on varying levels of emotion processing, with a particular focus on negative facial expressions. This transdiagnostic approach aims to capture RDoC's Negative Valence System and Systems for Social Processes. The term "neurodiverse" specifically describes children whose abilities, as observed by teachers, are accompanied by difficulties, highlighting their distinct cognitive, behavioural, and emotional profiles. Although the sample does not include children with formal diagnoses, many exhibit a higher likelihood of receiving a diagnosis in the future—some are awaiting referral, while others were diagnosed years after their initial participation in the study. This makes them a unique group where the transdiagnostic approach can be particularly beneficial, as it allows for the exploration of common underlying mechanisms among this neurodiverse sample.

Following this terminology, I used the term neurodiverse for children who are recruited via Neurodevelopmental Assessment Unit (NDAU) who have emotional, cognitive and/or behavioural difficulties in Chapter 4. In the following chapters 5 and 6, all children were included in one group at first and these children referred as at-risk since they include children with varying levels of emotional, cognitive and/or behavioural difficulties. Additionally, beginning in Chapter 4, I employed the RDoC framework to examine facial expression recognition abilities in children. This investigation spanned both neurotypical children and those with emotional, cognitive, and/or behavioural difficulties, creating a continuum of facial expression recognition skills at both behavioural and neurobiological levels.

1.8.1 The Cardiff University Neurodevelopmental Assessment Unit

In order to identify a diverse sample and adopt a transdiagnostic approach, the research in this thesis was conducted in collaboration with the Cardiff University Centre for Human

Developmental Science (CUCHDS) NDAU (https://www.cardiff.ac.uk/neurodevelopment-assessment-unit). The NDAU assesses children referred and identified by their teachers as exhibiting emotional, cognitive, and/or behavioural difficulties which require additional support or help, despite lacking any formal mental health diagnosis. These children underwent a comprehensive assessment of their social, cognitive, and emotional abilities through various behavioural assessments and questionnaires.

Importantly, the sample represents children with heightened levels of emotional, cognitive, and behavioural difficulties compared to their typical peers, but does not constitute a clinical population (Burley et al. 2022; Wells et al. 2020b). Studying such a sample, and adopting a transdiagnostic approach, allows for commonalities across various behavioural profiles to be identified, with the potential to provide better insight into common underlying mechanisms.

1.9 Overview of Thesis

This thesis first explores the influence of body context on facial expression recognition in a typically-developing sample of children, and in a neurodiverse sample of children who exhibit difficulties in emotional, behavioural and cognitive functions but do not have a clinical diagnosis, with a focus on mechanisms underlying the integration of body posture and facial expression signals. The second half of the thesis investigates structural brain networks supporting facial expression recognition, as well as functional networks in response to naturalistic emotional stimuli, across neurodiversity (see Figure 1.4 for an overview of thesis chapters).

In the current chapter, I provide a literature review, delving into facial expression recognition by expanding on development, neurodiversity, contextual influences, and neural mechanisms. Furthermore, I introduce the concept of a transdiagnostic approach, aimed at capturing a spectrum of specific behavioural characteristics, particularly facial expression recognition abilities. Chapter 2 explains the fundamentals of magnetic resonance imaging and its

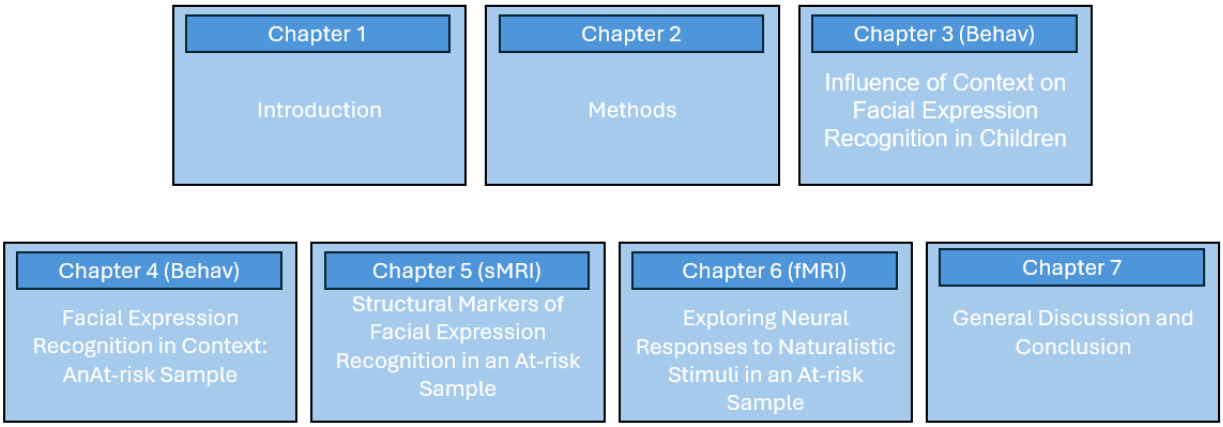

Figure 1.4: Thesis Overview.

modalities, which serve as the basis for the experimental chapters 5 and 6 in the thesis.

In the first experimental study, outlined in Chapter 3, the focus is on examining the pivotal role of contextual cues in shaping facial expression recognition among typically developing children. Here, I evaluate the emotion recognition abilities of these children, including isolated facial expression recognition, isolated body expression recognition, and facial expression recognition within a body context. The findings highlight the interconnectedness between facial expression recognition performance within a body context and their isolated facial expression recognition abilities, in alignment with existing research. I find that children were better at recognising facial expressions when paired with congruent body expressions compared to incongruent body expressions. Moreover, their ability to recognise isolated facial expressions is linked to their tendency towards body expression during facial expression recognition judgements in the context of a body posture.

In Chapter 4, I describe an experimental study looking at the influence of contextual cues on facial expression recognition, spanning both typically developing children, and those with emotional, cognitive, and/or behavioural difficulties. Mirroring the methodology of Chapter 3, the study evaluates performance in isolated facial expression recognition, isolated body expression recognition, and facial expression recognition within a body context. The findings reveal that children with emotional, cognitive, and/or behavioural difficulties demonstrate

diminished facial expression recognition abilities compared to their typically developing peers. Moreover, it is observed that the ability to recognise isolated facial expressions predicts the influence of body emotion on facial expression judgements, a consistent finding across both groups of children. These results suggest that despite difficulties in emotion recognition within a transdiagnostic sample of children with emotional, cognitive, and/or behavioural difficulties, the integration of emotional signals from the face and body operates under similar principles across all children, regardless of the level of emotional difficulties.

In Chapter 5, I investigate the structural underpinnings of facial expression recognition abilities across a neurodiverse sample of children, encompassing a community sample of typically developing children, and children with emotional, cognitive, and/or behavioural difficulties. The goal was to identify the shared structural markers of facial expression recognition across children exhibiting a spectrum of facial expression recognition abilities. Both traditional voxel-based morphometry and source-based morphometry approaches identified regions of grey matter variability linked to negative facial expression recognition ability. In particular, a network of grey matter covariance, which includes regions such as the middle temporal gyrus, premotor cortex, and middle and inferior frontal gyrus, was associated with negative facial expression recognition abilities. These findings underscore the presence of common underlying structural markers of facial expression recognition abilities within a neurodiverse sample.

In Chapter 6, the final experimental study examines the link between brain activation synchrony in response to an emotional movie and facial expression recognition abilities across a neurodiverse sample of children. All children exhibited synchronous brain activity in visual and auditory regions, line with prior studies using similar emotional stimuli. When comparing children with higher facial expression recognition abilities to those with lower recognition abilities, regions of inferior parietal lobe, frontal pole, medial frontal gyrus were found to exhibit higher synchronisation in children with lower facial expression recognition abilities. Conversely, the higher facial expression recognition ability children were characterised

by higher synchronisation in the ventromedial prefrontal cortex compared to lower facial expression recognition ability children. By building upon the findings of the previous chapter, this study suggests the presence of common and distinct underlying functional networks when viewing an emotional movie which are associated with facial expression recognition abilities across a neurodiverse sample.

In Chapter 7, the final chapter of the thesis, I summarise the findings of the thesis and discuss implications and methodological considerations, as well as future directions.

Chapter 2

General Methods

2.1 Magnetic Resonance Imaging

Magnetic Resonance Imaging (MRI) is a non-invasive imaging technique which allows for the visualisation of soft tissue anatomical structures and physiological processes within the body. The basis of MRI lies in the principles of nuclear magnetic resonance, wherein the protons of, typically, hydrogen atoms align with a static magnetic field. These hydrogen protons spin continuously, and they generate a small magnetic moment with random orientations due to their motion. When exposed to a strong external magnetic field (B0), these protons align themselves either parallel or antiparallel to B0. Most protons tend to align in parallel with B0 since it requires less energy. The consistent spinning motion exhibited by a group of protons is referred to as precession. The rate at which this precession occurs, indicating how frequently the protons precess per second, is referred to as the precession frequency, more commonly known as the Larmor Frequency (Currie et al. 2013; Fullerton 1982), which is related to the magnetic field strength. Higher magnetic fields lead to higher Larmor frequencies which improve the signal-to-noise ratio and spatial resolution (C. Liu & Li 2013; Brown et al. 2014). The image formation for MRI involves the application of radiofrequency excitation pulses which produces two key effects. Firstly, they supply additional energy to the parallel-

aligned protons leading them to an antiparallel alignment. Secondly, the radiofrequency pulse generates a magnetic field that exerts a torque on the protons, inducing them to precess in synchronisation with neighbouring protons in the transverse plane. Subsequently, this transverse magnetisation is detected and utilised to form MR images (Azhar & Chong 2023). Following their excitation, the protons begin to relax and return to a lower energy, equilibrium state. There are two key components to the relaxation process: the longitudinal relaxation time and the transverse relaxation time. The longitudinal relaxation time (T1) is a measure of how quickly protons return to their original equilibrium state. The transverse relaxation time (T2) is a measure of how quickly the protons in the transverse plane experience spin dephasing, causing rapid decay of transverse magnetisation immediately after the radiofrequency pulse excitation. Relaxation times differ across tissue types, leading to differential signal loss, and ultimately therefore image intensity.

2.2 Structural Magnetic Resonance Imaging

Structural MRI is dedicated to examining the structure of the brain, making it a valuable tool to detect structural changes, for instance lesions or tumours. Structural MRI also allows for the identification, visualisation, and quantification of brain morphometry, which measures brain structures, typically volume. As a result, structural MRI has been widely used in studying morphometric changes in neurological patients, as well as more diffuse psychiatric and neurodevelopmental conditions (Giedd & Rapoport 2010). The brain is predominantly made up of gray matter and white matter. Gray matter is the tissue type which contains neuronal cell bodies, dendrites, axons, neurons, glial cells (Martin 2006), whereas white matter is comprised of myelinated axons. Gray matter, which has many neurons, helps process, and transmit information through axon signals in the white matter. Distributed throughout the central nervous system, grey matter enables individuals to regulate movement, memory, and emotions (Chiao et al. 2020). Region-specific increases and decreases in gray matter volume have been found to correlate with various cognitive functions, clinical symptoms, and

developmental stages (Taki et al. 2013; Mancuso et al. 2020). Among the metrics used to study brain morphometry, gray matter is the most extensively studied, across neurotypical populations as well as in populations with mental health conditions. Structural MRI facilitates the visualisation and analysis of gray matter through volume-based approaches. Voxel-based morphometry is a well-established method for characterising local gray matter volume, while source-based morphometry is a newer approach focused on identifying networks of gray matter covariance across the brain (Backhausen et al. 2022).

2.2.1 Voxel-based Morphometry

VBM is an objective methodology that entails a voxel-wise comparison of the local concentration of gray matter. Prior to conducting any statistical analyses, structural MRI data undergo a series of preprocessing steps, including tissue segmentation, spatial normalisation, and smoothing. Tissue classification, based on image intensity distributions, is instrumental in distinguishing between gray matter, white matter, and cerebrospinal fluid. Subsequently, the normalisation step corrects for variations in brain size between individuals by ensuring voxel-by-voxel consistency across individuals. Smoothing is employed to reduce noise, thereby enhancing signal-to-noise ratio, and optimising statistical analysis (Ashburner & Friston 2000; Kurth et al. 2015). Following these preprocessing steps, VBM statistical analysis may encompass comparisons between two populations, such as individuals with autism, ADHD, or typically developing individuals (Nickel et al. 2018; M. X. Xu & Ju 2023). Alternatively, investigations may explore associations with behavioural measures, such as empathy or psychopathic traits (Eres et al. 2015; Lam et al. 2021). VBM has emerged as an extensively used method for detecting voxel-wise differences, providing precise anatomical localisation of volumetric changes in specific brain regions, and facilitating our understanding on the association between behaviour and the structure of brain regions.

2.2.2 Source-based Morphometry

SoBM, a more recently developed approach, captures large-scale patterns of covariation in structure across the entire brain. By employing Independent Component Analysis (ICA), SoBM facilitates a multivariate, data-driven analysis of brain structure, particularly gray matter volume, decomposing structural data into independent components (L. Xu et al. 2009). This methodological innovation confers notable advantages over VBM techniques, allowing for a more nuanced exploration of the interrelationship between voxels, the identification of brain regions with similar variations in grey matter volume, and no reliance on predefined regions or hypotheses. SoBM provides insights into the localization and covariation of gray matter changes across the brain. Moreover, the patterns identified through SoBM may exhibit close associations with functional networks, thereby providing insight into structure-function relationships in the brain (L. Xu et al. 2009; K. C. Wang et al. 2022).

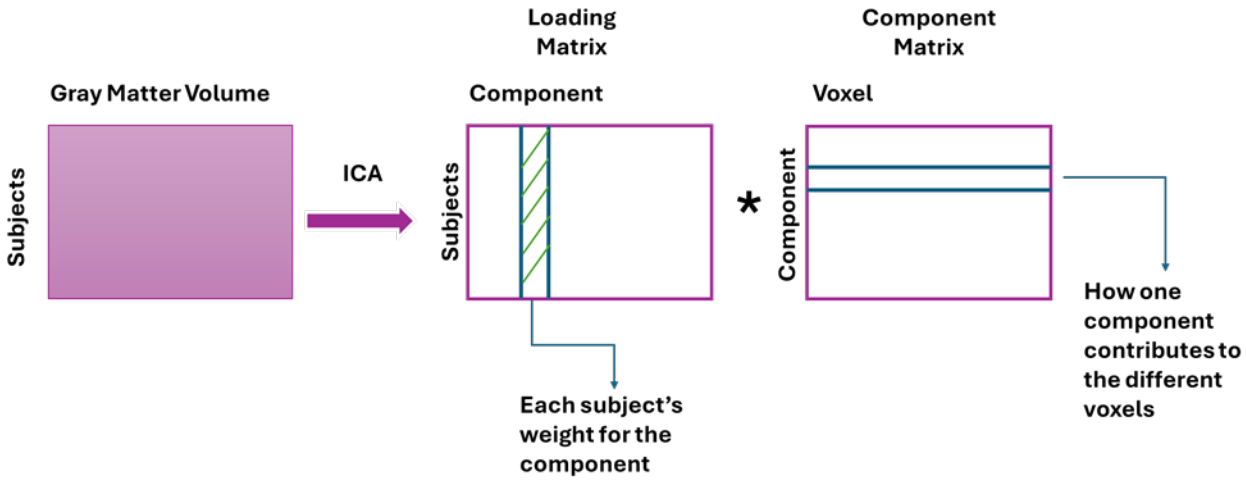

Figure 2.1: A generalised algorithm of source-based morphometry. Modified from Figure 2, Gupta et al. 2019.

SoBM analysis begins by flattening each individual's gray matter volume image and performing an ICA (Figure 1). ICA is a statistically powerful tool which transforms data into independent sources without prior information. This tool enables the disentanglement of mixed brain data into statistically independent components, thereby revealing underlying brain networks and elucidating patterns of structural covariation across individuals (Gupta et al. 2019;

K. C. Wang et al. 2022, L. Xu et al. 2009). ICA generates two distinct matrices for every identified independent component: the loading matrix and the component matrix. The loading matrix represents each individual's contribution to each of the identified independent components. The component matrix shows how a specific component contributes to the different voxels within the brain. Overall, the employment of network-level analysis in SoBM, complementing traditional region-of-interest approaches like VBM, holds promise for enhancing our comprehension of the complex interplay between brain structure and behaviour. By elucidating covarying structural relationships between brain regions, SoBM may contribute to a deeper understanding of potential structural markers that could underlie behavioural measures.

2.3 Functional Magnetic Resonance Imaging

Functional MRI is an application of MRI, that indirectly measures brain activity through regional changes in magnetisation resulting from increases in oxygenated blood flow to specific regions. The Blood Oxygen Level Dependent (BOLD) effect, which is the key metric in fMRI, serves as an indicator of alterations in brain activity, as it reflects the local metabolic demands of active neurons. When a brain region becomes more active, it requires heightened oxygen and glucose levels to fuel neuronal firing. This heightened demand prompts an increase in blood flow to the activated region, a phenomenon known as neurovascular coupling (Logothetis 2008; Phillips et al. 2016). The BOLD effect, which is linked to neural activity, occurs due to two distinct phenomena. Firstly, when haemoglobin, the oxygen-carrying molecule in blood, releases oxygen to become deoxyhaemoglobin, it undergoes a subtle change in magnetic properties. Deoxyhaemoglobin becomes paramagnetic, which in turn alters the magnetic susceptibility of blood. Secondly, increased neuronal activity leads to higher oxygen consumption. This results in a decrease in deoxyhaemoglobin (paramagnetic) and an increase in oxygenated haemoglobin (diamagnetic), thereby increasing the BOLD signal due to the inflow of oxygenated blood to the region. The change in the ratio between oxygenated

and deoxygenated haemoglobin results in changes to the magnetic properties of the blood, thereby impacting the local magnetic field that is detected by the MRI scanner. Through the measurement of magnetic property alterations, fMRI has the capability to indirectly map brain activity with exceptional spatial resolution (Buxton 2013). fMRI is widely used as a tool to study local brain function and functional connectivity across the brain, shedding light on neural activity associated with cognition, emotion, behavior, and mental health conditions (Deyoe et al. 1994; Gore 2003).

2.3.1 Inter-subject Correlation Analysis

Recent developments in fMRI analysis approaches, particularly within the realm of affective science, have witnessed a paradigm shift towards the utilisation of naturalistic stimuli. Such stimuli, including movies, audio clips, and real-life conversations, offer a more ecologically valid and immersive approach compared to traditional controlled tasks or passive viewing paradigms (Nastase et al. 2019; Saarimäki 2021). Inter-subject Correlation (ISC) has emerged as a powerful technique for examining continuous brain responses to dynamic stimuli across individuals. Within the context of naturalistic stimuli, brain activity measured by fMRI enables the identification of four distinct types of brain activity: shared responses to the stimulus, idiosyncratic responses to the stimulus, idiosyncratic activity unrelated to the stimulus, and noise. ISC provides a method to identify shared brain responses to stimuli across individuals, facilitating the comprehension of underlying neural responses to specific stimuli. It prioritises shared, common responses while minimising individual differences, this providing insights into shared neural processing (P. A. Chen et al. 2020; E. S. Finn et al. 2020; Hasson et al. 2004).

In traditional fMRI studies, the focus lies on examining brain activity in response to specific stimuli or during periods of resting-state, where brain is not engaged in any tasks allowing to measure spontaneous activity. This is typically achieved by comparing conditions, where the only difference between the conditions should be the measure of interest. However, the

current thesis takes a different approach, delving into fMRI time series data shared across participants, as well as between participants. This is achieved by correlating the brain activity of each participant across the whole time series of the scan among individuals. ISC analysis aims to focus on capturing the shared responses to the stimulus, which is revealed by BOLD signal time courses across individuals. This synchronisation observed in response to the naturalistic stimuli suggests that when presented with the same stimulus, the brains of different individuals "synchronise", exhibiting similar patterns of neural activity.

However, ISC approaches also enable the identification of brain activity patterns that differ significantly between groups of individuals, providing insights into differential neural mechanisms among individuals who differ in their cognitive, behavioural, or emotional abilities. In the current thesis, it allows for the identification of differing brain activity patterns across individuals according to facial expression recognition abilities. Separate ISC analyses are conducted on groups with different ability levels, enabling comparison of their shared neural responses. This approach enhances our comprehension of how brain activation synchrony in response to emotional stimuli may be related to relevant behavioural characteristics, like facial expression recognition ability. To conduct ISC analysis, the correlation between the time series data of every pair of individuals is computed throughout the entirety of the stimulus, e.g. movie clip. The Pearson correlation coefficient quantifies the level of similarity in neural responses among individuals (Hasson et al. 2004). To assess the significance of ISC values, groups can be compared using either permutation testing or bootstrap resampling methods. The significance of ISC values can then be determined following correction for multiple comparisons (Nastase et al. 2019; Nummenmaa et al. 2012).

By calculating the degree of neural synchrony across individuals, ISC offers a unique approach into the neural responses of shared experiences and individual differences in cognitive and affective processing. The implications of ISC analysis in elucidating shared neural responses to social cognition have, for example, been observed not only within healthy individuals, but also among those with autism, ADHD (Nummenmaa et al. 2012; Nummenmaa et al. 2018;

Salmi et al. 2013; Salmi et al. 2020).

In the realm of developmental populations, it is well-established that children often exhibit increased movement tendencies and reduced attentional capacities, with these challenges magnified among individuals with neurodevelopmental conditions (Raschle et al. 2009; Tziraki et al. 2021). When scanning children, there is a suggestion that using naturalistic stimuli, especially movies, can offer more comprehensive insights compared to traditional resting-state scans. One of the benefits of movies is that they can capture the diverse ways in which individuals process information and regulate their emotions, surpassing the restrictions imposed by artificial and controlled experiments/conditions (E. Finn & Bandettini 2020; Vanderwal et al. 2019). Moreover, individuals who are hard to scan, such as children, are known to move less during movie-watching scans compared to traditional resting-state scans (Greene et al. 2018; Vanderwal et al. 2019). Using movies during scanning procedures offers a chance to address the difficulties related to imaging populations that are hard to scan, ultimately improving the practicality and efficiency of neuroimaging research in developmental groups (E. Finn & Bandettini 2020).

Chapter 3

Influence of Context on Facial Expression Recognition in Children

3.1 Introduction

The recognition of emotions plays a crucial role in social and emotional development, facilitating the comprehension and navigation of social interactions. Traditionally, emotion recognition research has predominantly focused on isolated facial expressions, which have been extensively studied in both typical and clinical child cohorts (Cooper et al. 2020; McClure et al. 2003; Operto et al. 2020; Tonks et al. 2009). However, real-world interactions seldom involve isolated, full-intensity facial expressions. The focus on isolated facial expressions neglects the potential influence of contextual cues in one's perception of facial expressions. In light of this, some studies have investigated the significance of contextual cues, such as bodily expressions, to provide a more authentic reflection of emotion recognition in the real world (de Gelder 2009; van den Stock et al. 2007; Aviezer et al. 2008). In our daily social interactions, the body accompanies facial expressions as an important contextual cue, and research has shown that body expression has a significant influence on facial expression recognition (Aviezer et al. 2008). Both adults and children tend to exhibit a bias towards

body expressions when perceiving emotional facial expressions (Aviezer et al. 2012; Wieser & Brosch 2012; Mondloch 2012).

3.1.1 Facial Expression Recognition in the Context

In order to study the influence of body expression on facial expression recognition, researchers typically presented congruent and incongruent contextual emotion signals. Adults tend to have lower accuracy in facial expression recognition in the presence of incongruent body expressions relative to congruent body expressions, even when they are told to focus on the face and ignore the body (Aviezer et al. 2008; Perry et al. 2013). Additionally, adults exhibit a bias towards the body emotion in making their judgement of facial expressions (Aviezer et al. 2008; Meeren et al. 2005). This biasing influence of body expression in adults has been well documented, however, the influence of body expression on facial expression perception in children has not been well studied. To the best of my knowledge, there are only a few studies on how the presence of body expressions influences children's facial expression recognition.

Mondloch, Horner, & Mian (2013) conducted a study to examine how body expression influences facial expression recognition in children of different age groups, as well as in undergraduate students, even when children were instructed to concentrate on the face and ignore the body. Their findings showed that when body and facial expressions were congruent, children showed improved facial expression recognition compared with when face and body emotion were incongruent. Furthermore, this effect was present even in the youngest children. Children also exhibited a bias towards body emotion when making their judgement of facial expressions in the incongruent conditions. In a subsequent experiment, they also found that the influence of incongruent body contexts on their judgements of facial expression was not due to a limit in children's attentional capacity. Indeed, they showed a similar pattern of performance to adults. Also, children exhibit a greater impact of body emotions compared to adults.

The findings were supported by another study by Mondloch (2012), which found that 8-year-

old children and young adults have better performance in a facial expression recognition task when the body emotion is congruent with the facial expression compared with incongruent body cues. Both adult and child groups exhibited a comparable pattern of body expression influence on facial expression recognition. This again suggests that, like adults, children are influenced by incongruent body emotions during facial expression recognition. Similar to the previously mentioned study, the magnitude of the influence of body emotions was found to be larger in children than in adults.

In order to understand the mechanisms underlying facial expression and body posture emotion integration, Ward et al. (2023) found that the influence of body posture across development decreased with age, concurrently with an increased precision of isolated facial expression representations with age, pointing to a potential mechanism driving the influence of contextual cues such as body posture. However, their study was limited to the emotions of anger and disgust where they looked at children and adolescents between the ages of 8 and 18 years.

3.1.2 The Development of Facial Expression Recognition

Understanding how children perceive and interpret facial expressions as they grow and mature is of paramount importance for comprehending the intricacies of their social and emotional development (Goodman 1997; Herba & Phillips 2004). By examining the progression of facial expression recognition in children, we can gain valuable insights into how their abilities evolve over time and the factors that influence their perception of emotional cues. Early in development, children learn to recognise emotions, with facial expressions serving as their primary cues. As they progress from childhood to adulthood, their emotion recognition abilities improve, coinciding with the maturation of linguistic, cognitive, and social abilities (Kimonis et al. 2022). Throughout this developmental trajectory, children initially differentiate between positive and negative facial expressions (Herba & Phillips 2004; Kimonis et al. 2022; Parker et al. 2013; Ruba & Pollak 2020). Subsequently, the recognition of different facial expressions follows distinct developmental trajectories (Herba & Phillips 2004; Kimonis

et al. 2022; Widen 2013). Early in development, happy facial expressions are the first to be reliably recognised. However, the capacity to reliably differentiate negative emotions (e.g., anger, sadness, fear) occurs later in the course of development (Barisnikov et al. 2021; Herba & Phillips 2004; Witkower et al. 2021; Widen 2013), with anger and sadness reliably recognised at earlier ages than fear (Lawrence et al. 2015; Herba & Phillips 2004). Limited research has been conducted on the developmental trajectory of body expression recognition in childhood. Witkower et al. 2021 observed an age-related improvement in the ability to recognise body expressions among negatively valenced emotions. Parker, Mathis, & Kupersmidt (2013) established a positive association between children's proficiency in body expression recognition and their social skills. Collectively, these investigations indicate a parallel developmental trajectory between the recognition of body expressions and facial expression recognition, underscoring the significance of body expressions as crucial cues in children's social interactions.

3.1.3 The Current Study

Despite existing research into the influence of contextual cues on facial emotion recognition in children and how this differs from adults, it remains unclear how this influence develops during childhood and what mechanisms might drive the influence of body posture on facial expression recognition. The main objectives of the current study were to investigate the influence of body expressions on facial expression recognition in children aged 4-10, and to assess whether children's isolated facial and body expression emotion recognition skills predict the influence of body expression on facial expression recognition.

3.2 Methods

3.2.1 Participants

The study sample included 80 (36 male) typically developing children aged 4 to 10 years (M = 7.27, SD = 1.73) recruited from the UK (primarily South Wales). Recruitment and data collection were conducted online due to COVID-19 restrictions on in-person testing. The participants were recruited through advertisements on social media platforms like Facebook and WhatsApp, as well as university platforms such as Yammer and Cardiff University Brain Research and Imaging Centre (CUBRIC)'s weekly email newsletter. The study was approved by the Cardiff University School of Psychology Research Ethics Committee. The participants were given a £10 gift voucher as a token of appreciation for their participation.

3.2.2 Materials

Demographics The demographics information collected included age in years and months, gender and the relation of the participant who filled out the questionnaires (e.g., mother, father, or carer).

Strengths and Difficulties Questionnaire (SDQ) The Strengths and Difficulties Questionnaire (SDQ) was developed by Goodman 1997 to assess the emotional and behavioural problems of children. The parent report version of the questionnaire used in the current project included items to assess emotional problems, conduct problems, hyperactivity, peer problems, and prosociality across twenty-five items using a 3-point Likert scale (0= "not true," 1= "somewhat true," 2= "certainly true"). The scoring of the SDQ allows for the calculation of internalising and externalising scores by combining responses on the emotional and peer problems scales, and on the conduct and hyperactivity scales, respectively. The test-retest reliability of the SDQ is high: .85 for Total SDQ score (Achenbach et al. 2008). There is also good internal consistency, with Cronbach's alpha values ranging from .63 to .85 (Deighton et

al. 2014; Haywood et al. 2014).

Emotion Recognition Tasks

The study included three behavioural tasks: an isolated Facial Expression Recognition (FER) task, an isolated Body Emotion Recognition (BER) task, and a Whole-person Emotion Recognition (WPER) task.

Facial Expression Recognition Task Facial expression stimuli included angry, happy, sad, and fearful expressions of 2 male and 2 female faces. The neutral faces included a further four (two female) additional identities, for a total of 8 identities. Stimuli were selected from the Radboud Facial Expression Database (Langner et al. 2010). High-intensity facial expressions were the original facial expressions from the database, and low-intensity facial expressions were created by morphing each high intensity emotional expression (100%) with a neutral expression from the same identity (0%) to obtain morph levels between 50% and 75% (Hunnikin et al. 2020; Paine et al. 2021).

Body Emotion Recognition Task Emotional body stimuli were selected from a validated postural database (Lopez et al. 2017). Two stimuli for each emotional body expression of anger, joy, sadness, and fear were selected from two male identities. The clothing of the body expression stimuli was edited to create eight identities.

Whole-person Emotion Recognition Task Whole person stimuli were created using GIMP 2.10.22 by combining the male body expressions (Lopez et al. 2017) with male facial expressions (Tottenham et al. 2009; Langner et al. 2010) for each emotion category of anger, happiness, sadness, and fear. Initial piloting showed that the task was too long for children to use the full complement of stimuli, including all combinations of face and body emotions. I therefore chose to concentrate on angry and sad facial expressions that are recognised earlier during development than fear, but later than happy faces (Herba & Phillips 2004).

For the facial expressions of anger and sadness, each of the four male identities were paired with one of the body expressions for each emotional category (anger, happiness, sadness, and fear), resulting in 32 stimuli. In contrast, for happy and fearful facial expressions, one different identity, combined with one version of the body expressions, resulting in eight stimuli for these emotions. In total, there were 40 stimuli for this task. The whole person stimuli included twelve congruent (e.g., the combination of happy facial expression and happy body expression) and twenty-eight incongruent (e.g., the combination of sad facial expression and angry body expression) trials.

Every trial in each task included the presentation of a stimulus for two seconds followed by the appearance of the emotional label response prompts; angry, happy, sad, and scared (for the FER task, this also included 'no feeling'). Responses were recorded by mouse-click. Response was self-paced. There was a three-second intertrial interval before the next stimulus was shown (Figure 3.1).

3.2.3 Procedure

An online information sheet and consent form were obtained from the parents via Qualtrics (Qualtrics, Provo, UT). The parent was asked to sit with their child during the tasks but was asked not to suggest any particular response. The presentation order of FER and BER tasks was randomized, but the WPER was always the last task, to ensure that all children had equal exposure to the facial and bodily expressions of emotion before completing the WPER task.

The experiments were designed in PsychoPy 2021.1.2. (Using Python version 3.6) to create facial expression recognition, body emotion recognition, and whole-person emotion recognition tasks (Foul et al. 2018; Mondloch 2012; Mondloch, Horner, & Mian 2013). An audio version of the instructions was played alongside the written instructions for each task. The tasks were hosted online via Pavlovia (Open Science Tools,Nottingham,UK).

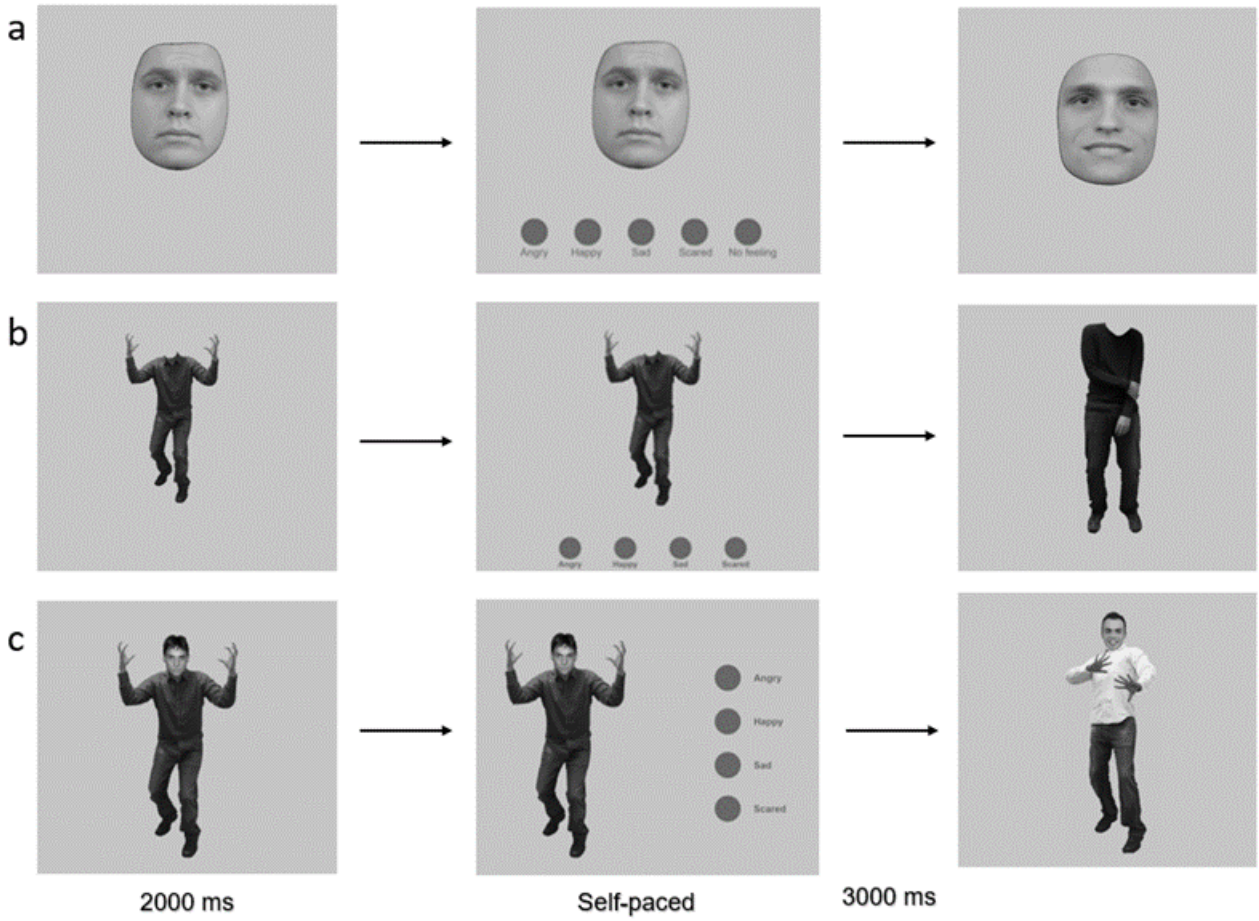

Figure 3.1: The design of the FER task (a), BER task (b), and WPER task (c). (a) The left and middle image is an example of a sad facial expression, and the right image is a happy facial expression. (b) The left and middle image is an example of an angry body expression, and the right image is a sad body expression. (c) The left and middle image is an example of a congruent trial with an angry face and angry body expression, and the last image is an incongruent trial with a happy face and fearful body expression. Each stimulus was shown for 2 seconds, followed by the appearance of response prompts. The task was self-paced, and the next stimulus appeared 3 seconds after the response was recorded.

To make the tasks more child-friendly, the FER task included a narrative about collecting treasure chests as the participants completed the task. The task started with five practice trials without any feedback before the actual task started. Every four trials another treasure chest was added to a tally screen that was presented to the child, and by the end of the task, the children had collected ten treasure chests in total. The appearance of treasure chests was not associated with performance. The FER task was approximately 8 minutes long.

The BER task narrative informed children that they were detectives and had to figure out

how people felt from their bodies. They were told that a thief had stolen the faces; this narrative was based on a similar narrative from Mondloch 2012. The task was launched with four practice trials with feedback to ensure that children understood the task. The participants collected stars throughout the task, with one star awarded for every four trials. The task duration was 5 minutes.

Helping SpongeBob and Patrick catch jellyfish was the narrative used for the WPER task. Initially, four practice trials were presented without any feedback. The stimulus presentation order was pseudorandomized, with no identical facial identity presented in succession. WPER instructed children to focus on the face and ignore the body when they decided how the person was feeling. The task duration was approximately 10 minutes.

3.2.4 Data Analysis

The data retrieved from Qualtrics (Qualtrics, Provo, UT) and Pavlovia (Open Science Tools, Nottingham, UK) were merged into an Excel file. The plots were created using MATLAB 2022b (Natick, Massachusetts: The MathWorks Inc. https://www.mathworks.com), RStudio Version 2023.06 (RStudio, PBC, Boston, MA URL http://www.rstudio.com/), and JASP 0.18.0 (JASP Team, https://jasp-stats.org/) and all statistical analyses were carried out in RStudio and JASP 0.18.0.

For emotion recognition accuracy, facial expression recognition accuracy was calculated for each emotion and intensity level with accuracy scores between 0 (least accurate) and 1 (most accurate). Neutral faces were excluded from the overall facial expression recognition accuracy scores. Similar scoring for body expression recognition accuracy was calculated for each emotion.

A body bias index was calculated for angry and sad facial expressions in the WPER task, to determine the influence of body expression on angry and sad facial expression perception. A higher body bias index indicates a greater influence of body expression on facial expression

recognition and vice versa. Bias indices were calculated using the following formulae.

Body Bias Index (Angry faces):

$$\frac{\left(\frac{\text{HR in AH trials}}{\text{HR in AH trials+AR in AH trials}}\right)+\left(\frac{\text{SR in AS trials}}{\text{SR in AS trials+AR in AS trials}}\right)+\left(\frac{\text{FR in AF trials}}{\text{FR in AF trials+AR in AF trials}}\right)}{3} \tag{3.1}$$

Body Bias Index (Sad faces):

$$\frac{\left(\frac{\text{AR in SA trials}}{\text{AR in SA trials+SR in SA trials}}\right)+\left(\frac{\text{HR in HS trials}}{\text{HR in SH trials+SR in HS trials}}\right)+\left(\frac{\text{FR in SF trials}}{\text{FR in SF trials+SR in SF trials}}\right)}{3} \tag{3.2}$$

*AR = Anger Responses; HR = Happiness Responses; SR = Sadness Responses; FR = Fear Responses; AH = Angry Facial Expression and Happy Body; AS = Angry Facial Expression and Sad Body; AF= Angry Facial Expression and Fearful Body; SA = Sad Facial Expression and Angry Body; SH = Sad Facial Expression and Happy Body; SF= Sad Facial Expression and Fearful Body;.

Where data were non-normally distributed, non-parametric tests were used.

3.3 Results

3.3.1 Demographics and Questionnaires

Demographic and behavioural characteristics of typically developing children are shown in Table 3.1. The current sample exhibited emotional and behavioural profiles characterised by scores with the mean of 16.4) on the SDQ total score, as determined by a previously established cut-off score of 17, which was derived from a UK-normative study (Meltzer et al. 2003).

Whole Sample N=80	**Mean (SD)**
Demographics	
Age (years)	7.26 (1.72)
Gender (Female %)	44 (55%)
Conduct Problems	5.50 (1.31)
Hyperactivity	5.85 (1.20)
Emotional Problems	3.04 (1.36)
Peer Problems	2.04 (1.78)
Prosocial	5.58 (1.62)
Total SDQ	16.4 (3.48)
Internalizing Problems	5.08 (2.81)
Externalizing Problems	11.3 (2.08)

Table 3.1: Descriptive Statistics of Demographics and Behavioural Measures. The means for each variable are presented with standard deviations in brackets.

3.3.2 Isolated Emotion Recognition

Isolated Facial Expression Recognition

A positive, significant correlation between overall FER accuracy and age suggests that, as expected, children's facial expression recognition accuracy increases with age (ρ=0.36 $p < 0.001$,Figure 3.2).

A one-way repeated-measures ANOVA showed a significant main effect of emotion among typically developing children, with differences between the recognition accuracy of different facial expressions ($F(2.84,\ 224.02) = 17.37$, $p < 0.001$; Greenhouse-Geisser corrected). Bonferroni corrected post-hoc comparisons showed that recognition accuracy for happy facial expressions was significantly higher than that for angry, sad, and fearful facial expressions (all p's < 0.001), whereas the other emotion categories did not show any significant difference from each other (Figure 3.3).

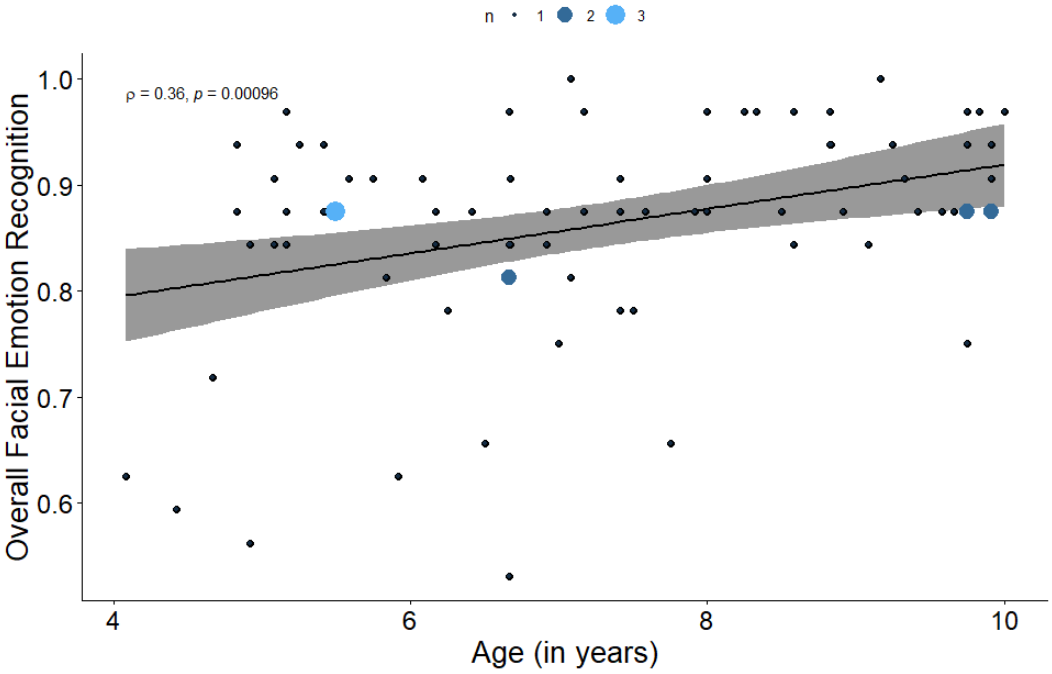

Figure 3.2: The Link Between Overall Facial Expression Recognition and Age. A positive correlation was identified between overall facial expression recognition and age in years (ρ=0.36 $p < 0.001$). The 95% confidence interval is shown with light grey shading. The size of each datapoint represents the number of participants at that particular point.

Isolated Body Emotion Recognition

Overall BER accuracy and age showed a positive significant correlation ($\rho = 0.39$, $p < 0.001$) indicating that older children are better at recognising body emotions than younger children (Figure 3.4).

Using the Greenhouse-Geisser correction, a one-way repeated-measures Analysis of Variance (ANOVA) showed a significant main effect of body emotion, with differences between the recognition accuracy of different body expressions, $F(2.71, 214.2) = 22.82$, $p < 0.001$. Bonferroni-corrected post-hoc comparisons revealed a significant difference between angry body expression recognition accuracy and both happy body expression ($p < 0.001$) and sad body expression recognition ($p < 0.001$). Fearful body expression recognition accuracy was significantly different from both sad body expression ($p < 0.001$) and happy body expression ($p < 0.001$) recognition accuracies (Figure 3.5).

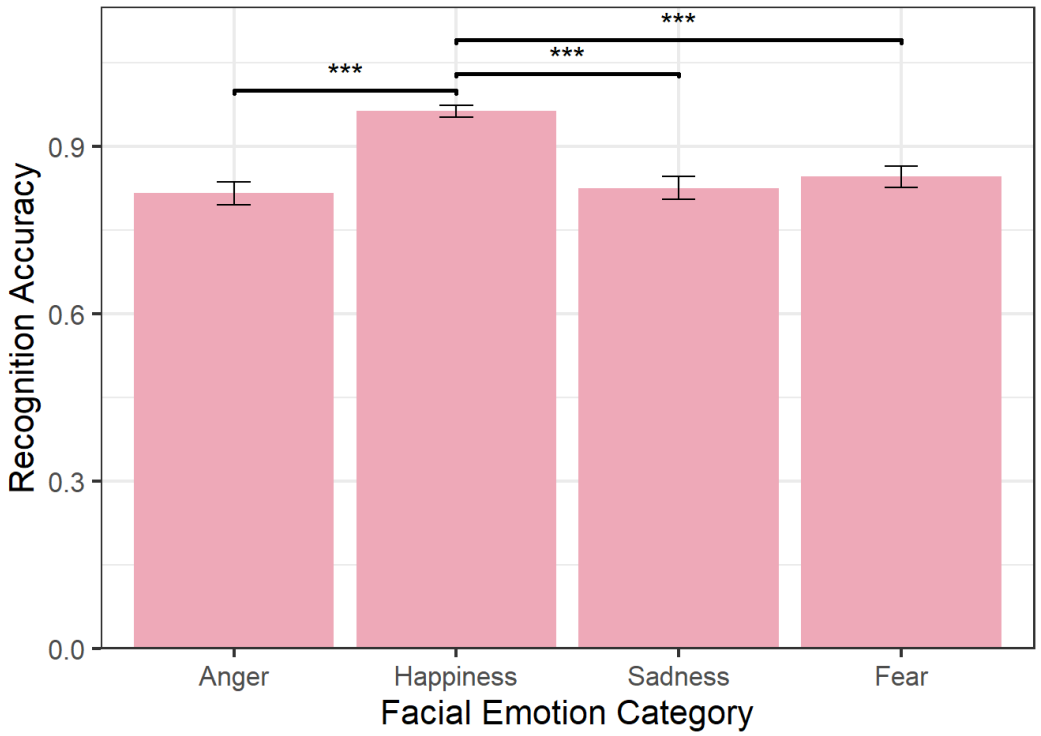

Figure 3.3: Facial Expression Recognition Accuracy by Emotion. *** indicates a significant difference at $p < 0.001$.

3.3.3 Facial Expression Recognition in the Body Context

Facial Expression Recognition Accuracy

A paired t-test showed that the facial expression recognition accuracy for congruent trials was significantly higher than for incongruent trials in the WPER task $t(79)=9.2, p < 0.001$ (Figure 3.6), illustrating that incongruent body expressions decrease children's facial expression recognition accuracy relative to congruent body expressions.

In accordance with Mauchly's sphericity violation of the data, using Greenhouse-Geisser correction, a one-way repeated-measures ANOVA was conducted to compare the recognition accuracy for isolated angry facial expressions, congruent and incongruent trials of WPER task with angry facial expressions. There was a significant main effect of the trial type among children, $F\ (1.679,\ 132.673) = 49.667$, $p < 0.001$. Bonferroni-corrected post-hoc tests showed that children benefit from the inclusion of a congruent body expression and

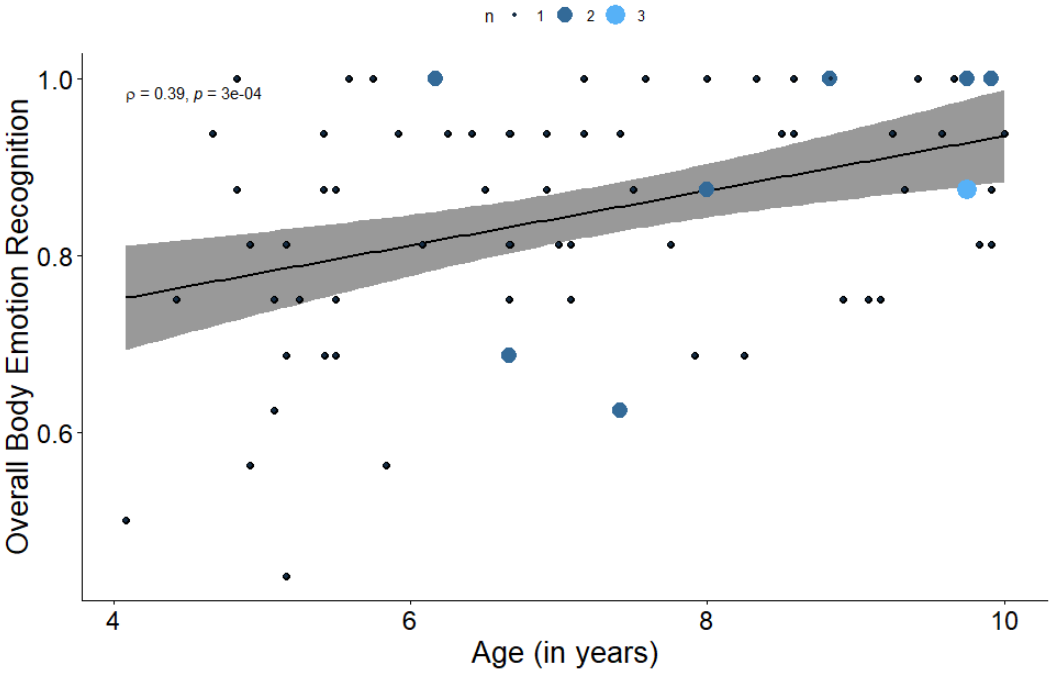

Figure 3.4: Relationship between Overall Body Emotion Recognition and Age. A significant positive correlation was identified between overall body posture emotion recognition and age in years ($\rho = 0.39$, $p < 0.001$). The 95% confidence interval is shown with light blue shading. Each point represents one subject, and the size of each point represents the number of subjects included in the particular data point.

perform significantly better in the congruent face-body trials than in the isolated angry facial expression trials ($p < 0.001$) and trials with an incongruent body emotion ($p < 0.001$). Facial expression recognition accuracy was significantly higher in the congruent trials than in incongruent trials ($p < 0.001$), indicating that the presence of a mismatching body expression negatively influenced their performance (Figure 3.7).

To investigate whether the recognition of high- and low-intensity isolated facial emotions differed from congruent and incongruent trials, I conducted a one-way repeated measures ANOVA for both angry and sad facial expression trials. Using the Greenhouse-Geisser correction, I found a significant main effect of trial type for angry facial expressions across high- and low-intensity, as well as congruent and incongruent trials, F (2.644, 208.9) = 28.97, $p < 0.001$. Bonferroni-corrected post-hoc tests revealed that accuracy was significantly higher for congruent trials compared to incongruent and both high- and low-intensity angry facial

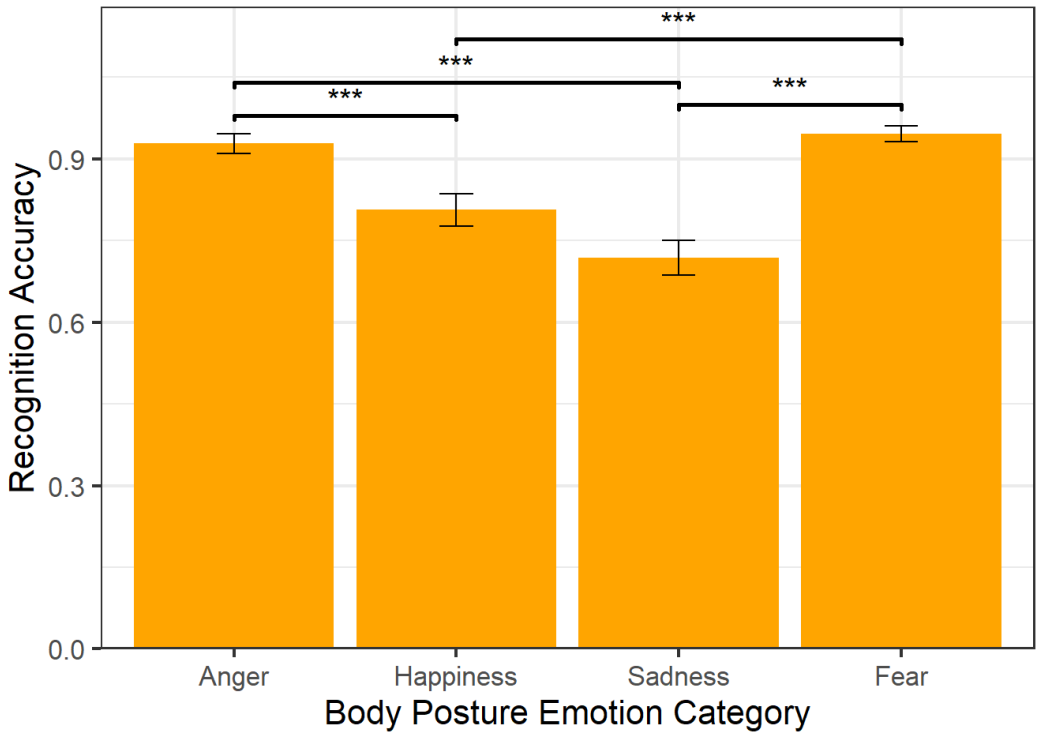

Figure 3.5: Body Emotion Recognition Accuracy by Emotion. *** indicates a significant difference at $p < 0.001$.

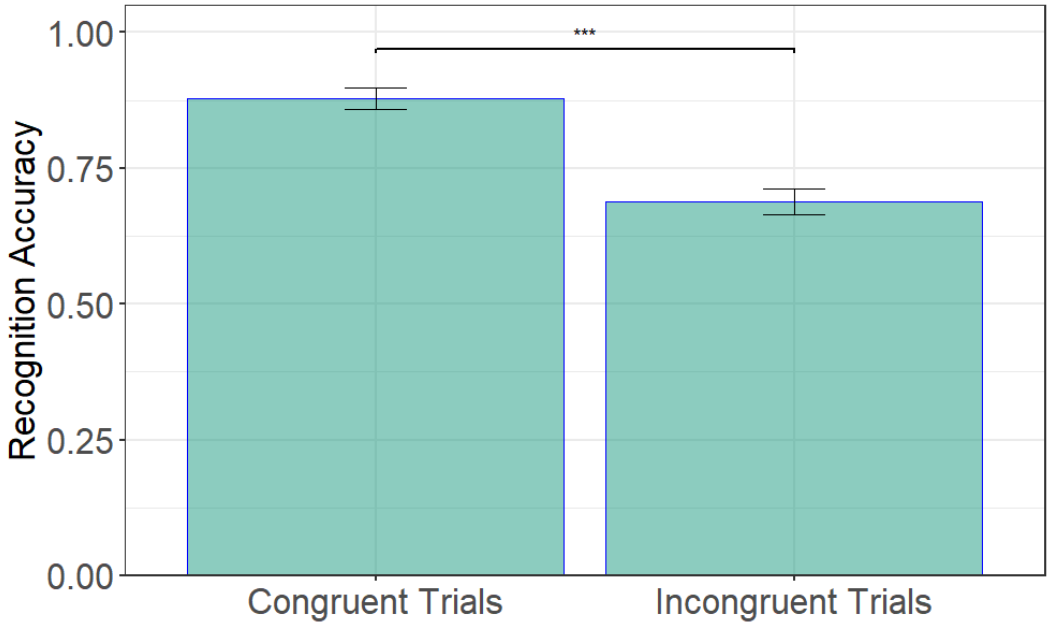

Figure 3.6: The Comparison of Accuracy in Congruent and Incongruent Trials. *** indicates significant difference at $p < 0.001$.]

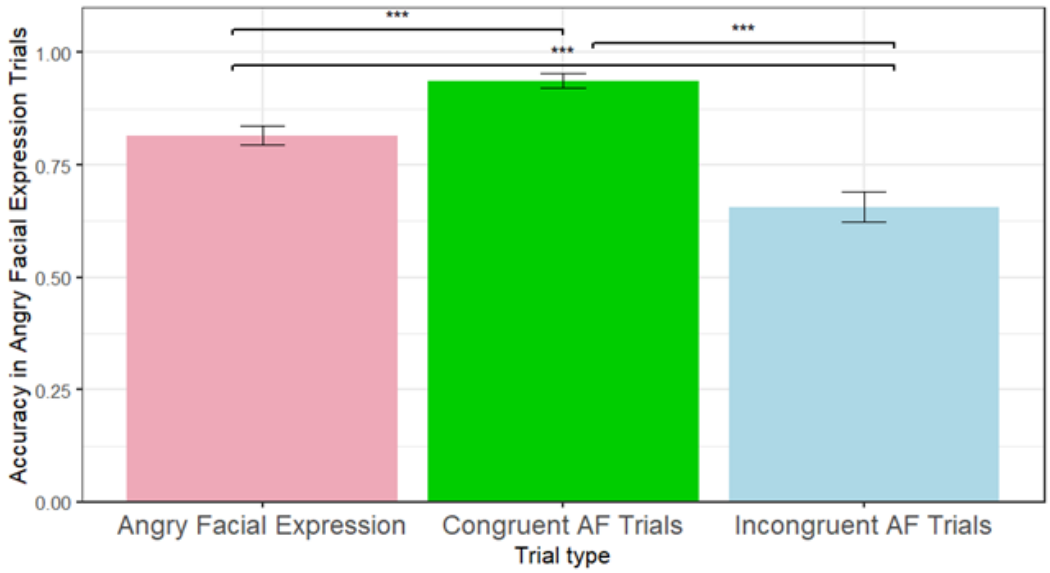

Figure 3.7: Facial Expression Recognition Accuracy for Isolated Angry Facial expressions, Congruent and Incongruent Angry Facial Expression Trials.

expression trials, $p's < 0.001$. Additionally, accuracy in incongruent trials was significantly lower than in both high- and low-intensity trials, $p's < 0.001$, but there was no difference between high- and low-intensity recognition performance, $p = 1$.

For sad facial expressions, there was also a significant main effect of trial type, using the Greenhouse-Geisser correction, F (2.11, 166.99) = 25.78, $p, 0.001$. Accuracy in congruent sad facial expression trials was significantly higher than in incongruent trials, $p, 0.001$, but lower than in high-intensity sad facial expression recognition, $p = 0.008$. High-intensity sad facial expression recognition was significantly better than both incongruent ($p < 0.001$) and low-intensity trials ($p < 0.001$). Low-intensity sad facial expression recognition was significantly better than incongruent trials ($p < 0.001$), but there was no difference between congruent and low-intensity recognition performance, $p = 1$.

The same analyses were conducted for the sad facial expression trials (Figure 3.8). There was a significant main effect of trial type on sad facial expression recognition performance of children, F(1.62, 128.25) = 23.65, $p < 0.001$. Bonferroni corrected post-hoc comparisons showed that children were better at recognising isolated sad facial expressions compared with

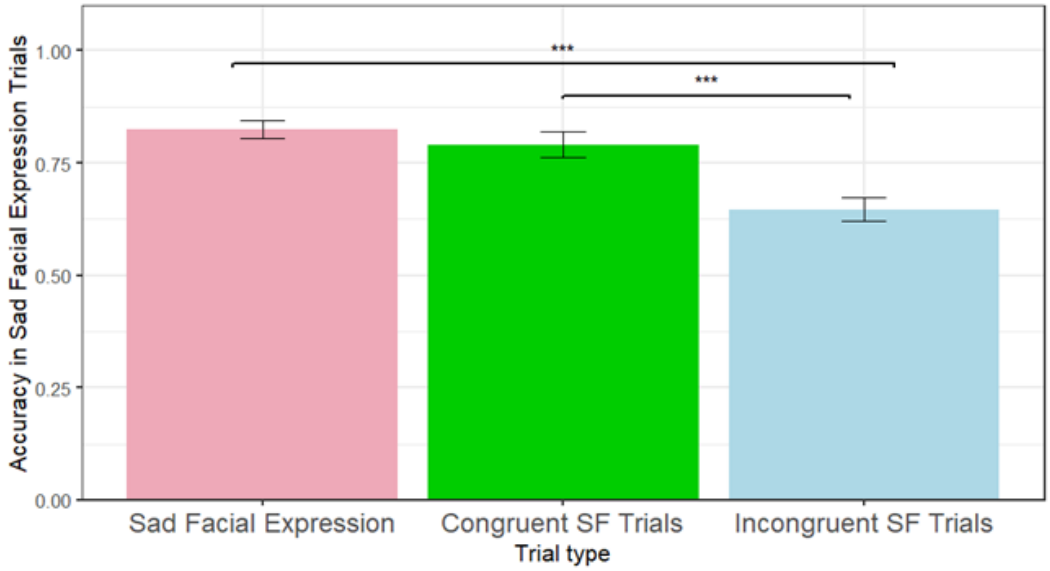

Figure 3.8: The Accuracy Comparison for Isolated FER, Congruent, and Incongruent WPER of Sad Facial Expression Trials.

sad facial expressions with an incongruent body expression ($p < 0.001$), but not sad facial expressions in the context of a sad body expression. Moreover, facial expression recognition performance in congruent trials was higher than that in incongruent sad facial expression trials ($p < 0.001$).

Biasing Influence of Body Expression on Facial Expression Recognition

Angry Facial Expressions

A 2 (response type) x2 (body type) repeated-measures ANOVA of angry facial expression trials in the WPER task revealed a significant main effect of response type ($F(1,79) = 532.498$, $p < 0.001$), and body type ($F(1,79) = 47.751$, $p < 0.001$). Here, response type refers to accurate facial expression responses ('rated as anger'), or 'rated as other/as body' responses which include both non-anger responses for congruent trials (angry face-angry body) and 'as body' emotion responses for incongruent trials, whereas body type refers to congruent and incongruent body emotions. There was a significant interaction between response type and body type, $F(1,79) = 77.404$, $p < 0.001$. Bonferroni-corrected post-hoc tests showed that

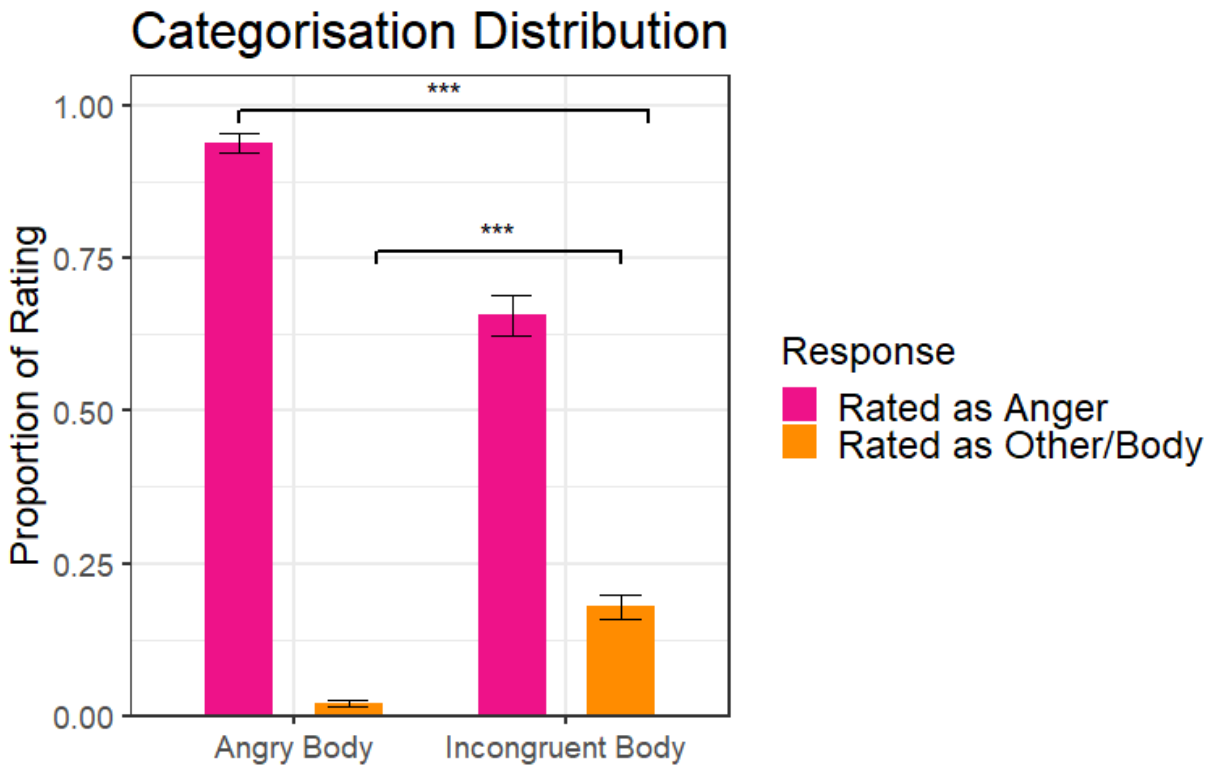

Figure 3.9: The proportion of ratings 'as face' emotion and 'as other/as body' emotion for all angry facial expression trials.
*** identifies $p < 0.001$, according to the Bonferroni-corrected post hoc tests.

there were significantly more anger responses in the angry body (congruent) context than in the incongruent body contexts ($p < 0.001$). Similarly, there were significantly more 'as body' responses in the incongruent body trials than there were other non-anger responses for congruent angry face and angry body trials. ($p < 0.001$, Figure 3.9).

Sad Facial Expressions

A similar 2x2 repeated-measures ANOVA for sad facial expression trials revealed a significant main effect of response type ($F(1,79) = 266.659$, $p < 0.001$, but there was no main effect of body type ($F(1,79) = 0.052$, $p = .820$). Importantly, a significant interaction between response type and body type was observed ($F(1,79) = 60.101$, $p < 0.001$.

Bonferroni-corrected post-hoc tests showed significant differences between sad responses

for sad facial expressions in a sad body context and those for sad facial expressions in an incongruent body context ($p < 0.001$). Similarly, significant differences were observed between non-sad responses in the sad body context and as body responses in the incongruent body context ($p < 0.001$, Figure 3.10).

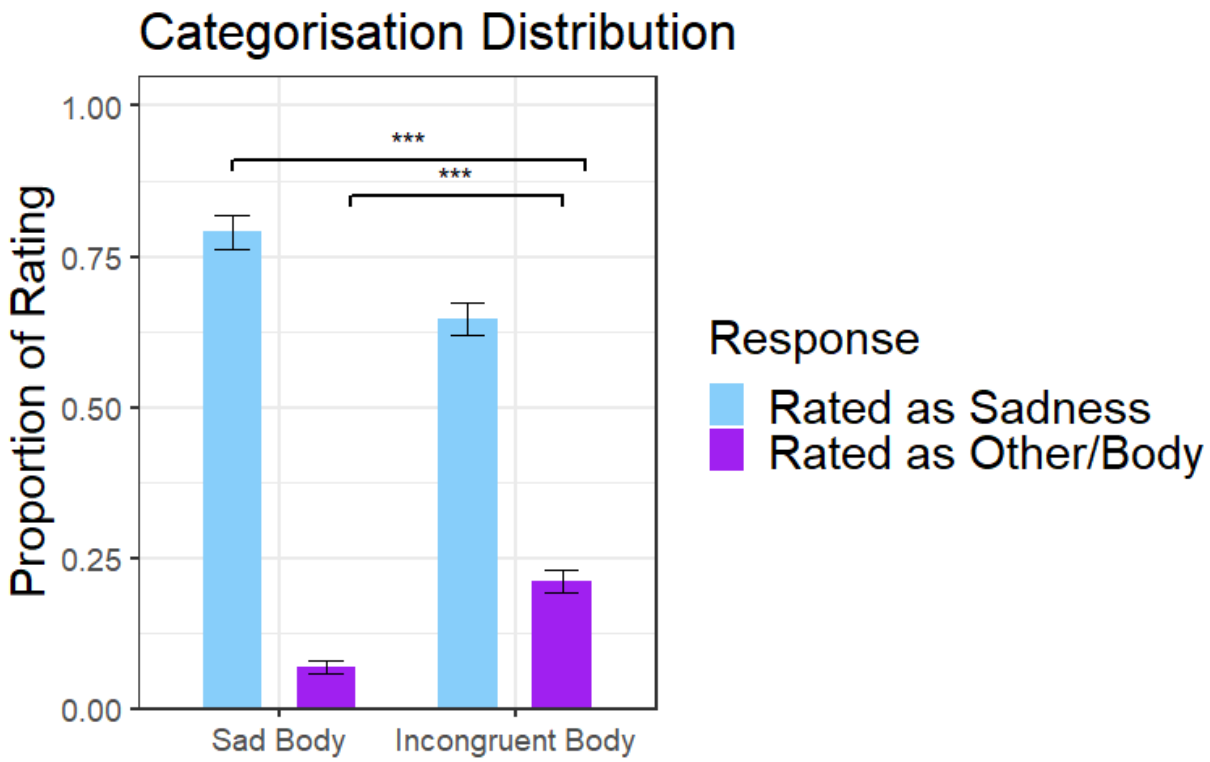

Figure 3.10: The proportion of ratings 'as face' emotion and 'as other/as body' emotion for sad facial expression trials.
*** identifies $p < 0.001$, according to the Bonferroni-corrected post hoc tests.

3.3.4 Body Bias, Age, and Facial Expression Recognition

Here, I investigated the relationship between the extent of influence of body emotion, isolated facial expression recognition, and age.

Body Bias and Facial Expression Recognition

The body bias for angry facial expression trials was significantly negatively correlated with isolated angry facial expression recognition performance ($\rho = -0.31$, $p = 0.0079$; controlling

for age, $\rho = -0.34$, $p = 0.002$; Figure 3.11), suggesting that children are less influenced by the body emotion in making judgements about facial expressions if they are better at recognising isolated angry facial expressions. Conversely, for sad facial expression trials, there was no relationship between body bias and isolated sad facial expression recognition accuracy ($\rho = -0.098$, $p = 0.4$; controlling for age, $\rho = -0.05$, $p = 0.65$; Figure 3.12).

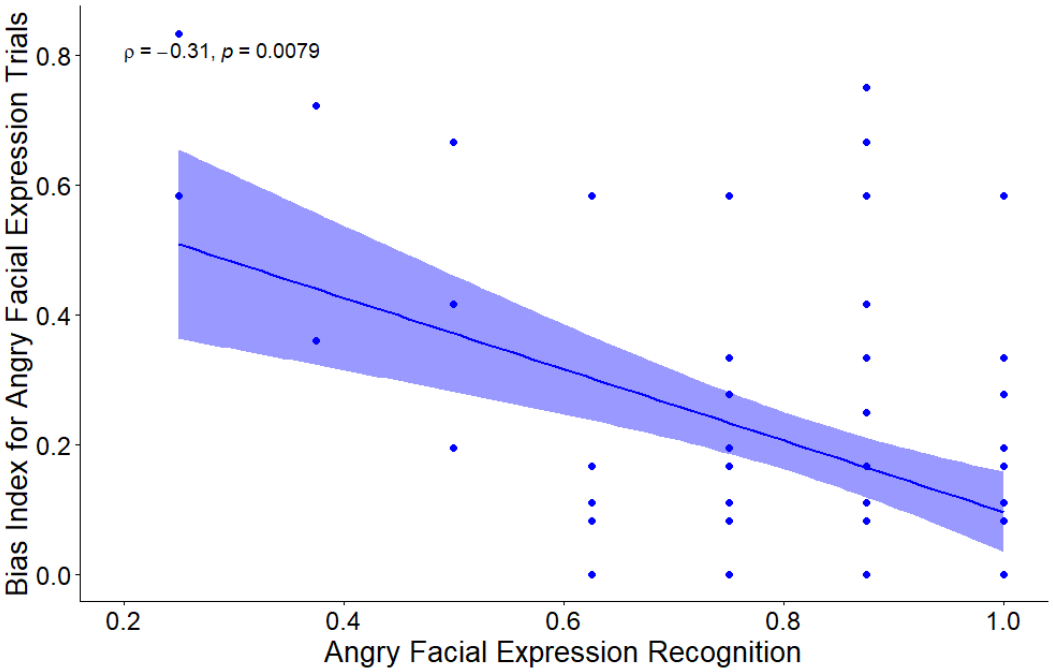

Figure 3.11: Relationship Between Body Bias for Angry Facial expression Trials and Isolated Angry FER.
Each point represents one child. Shaded area represents the 95% confidence interval.

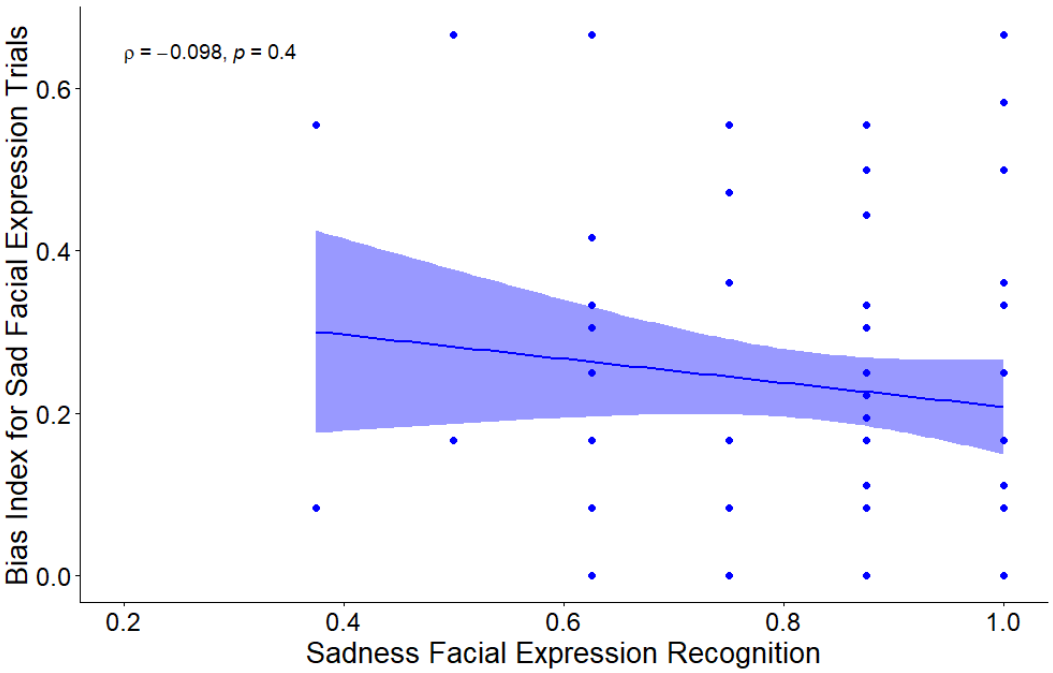

Figure 3.12: Relationship Between Body Bias for Sad Facial expression Trials and Isolated Angry FER.
Each point represents one child. Shaded area represents the 95% confidence interval.

Body Bias and Age

The body bias index for angry facial expressions (Figure 3.13) did not reveal a significant correlation with age ($\rho = -0.19$, $p = 0.11$) whereas for sad facial expressions (Figure 3.14) showed a significant, negative correlation with age ($\rho = -0.23$, $p = 0.04$). This indicates that older children are less likely to be influenced by body posture in their judgements of sad facial expressions than younger children.

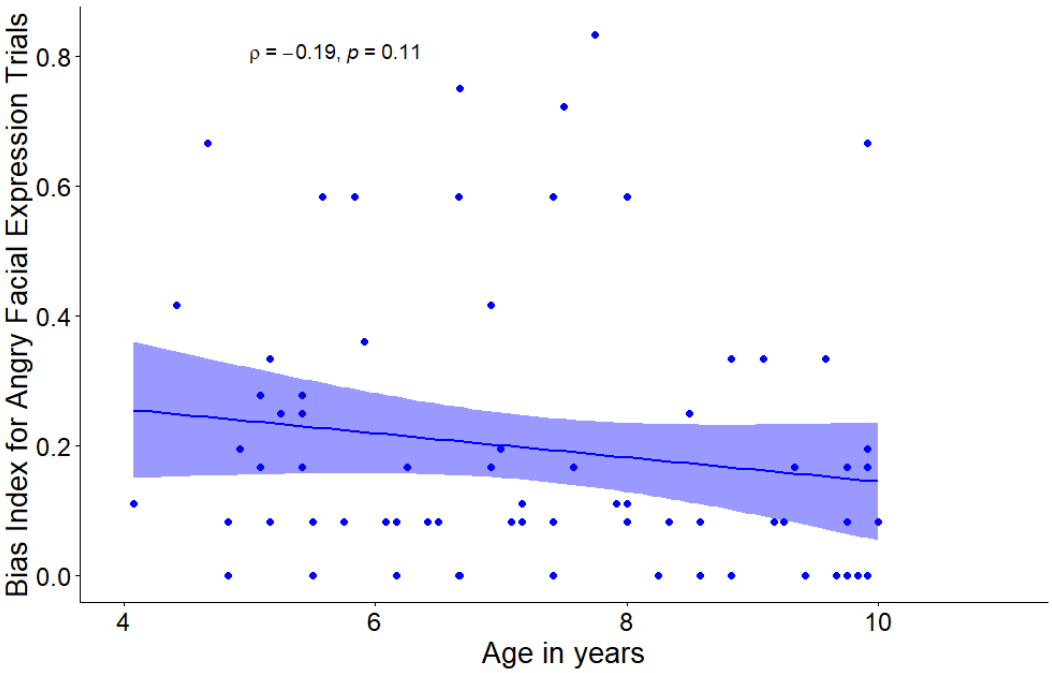

Figure 3.13: Relationship Between Age in Years and Body Bias for Angry Facial Expression Trials.
Each point represents one child. Shaded area represents the 95% confidence interval.

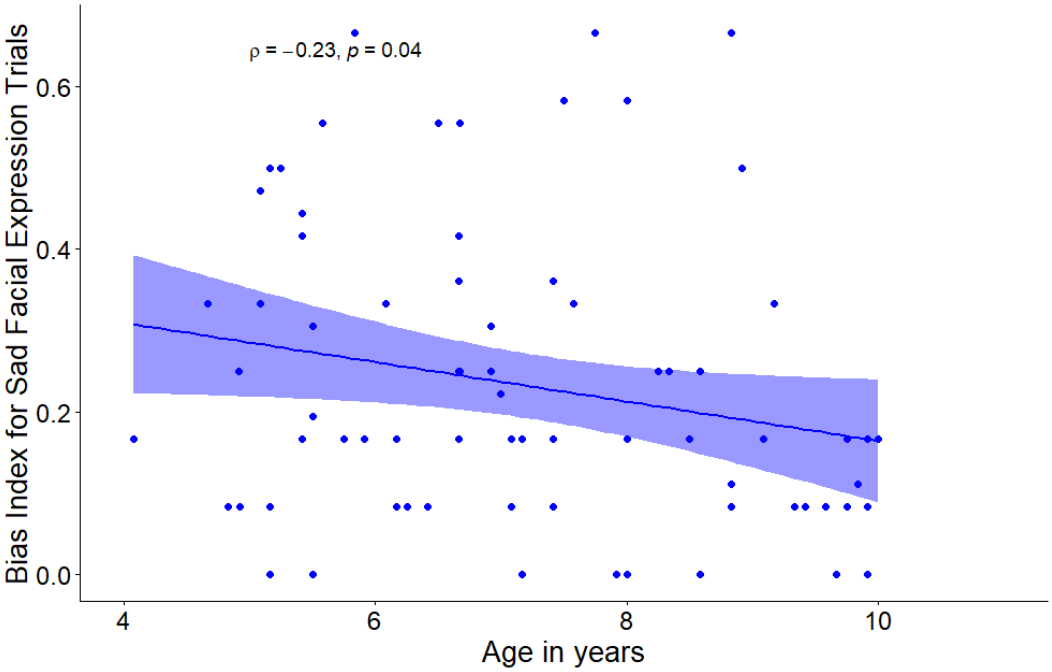

Figure 3.14: Relationship Between Age in Years and Body Bias for Sad Facial Expression Trials.
Each point represents one child. Shaded area represents the 95% confidence interval.

Facial Expression Recognition and Age

Children showed a positive trend with age for isolated angry facial expression accuracy ($\rho = 0.22$, $p = 0.049$) (Figure 3.15). There was a significant, positive correlation between age and isolated sad facial expression accuracy, $\rho = 0.26$, $p = 0.02$ (Figure 3.15), such that older children were significantly better than younger children at accurately recognising isolated sad facial expressions.

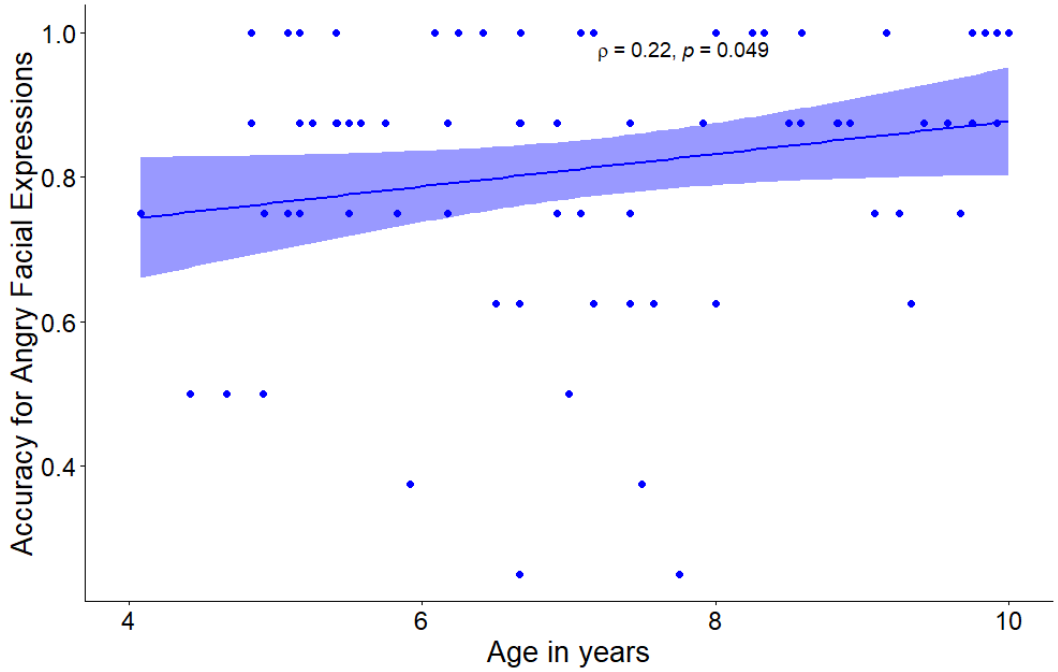

Figure 3.15: The relationship between isolated angry facial expression recognition and age. Each point represents one child. Shaded area represents the 95% confidence interval.

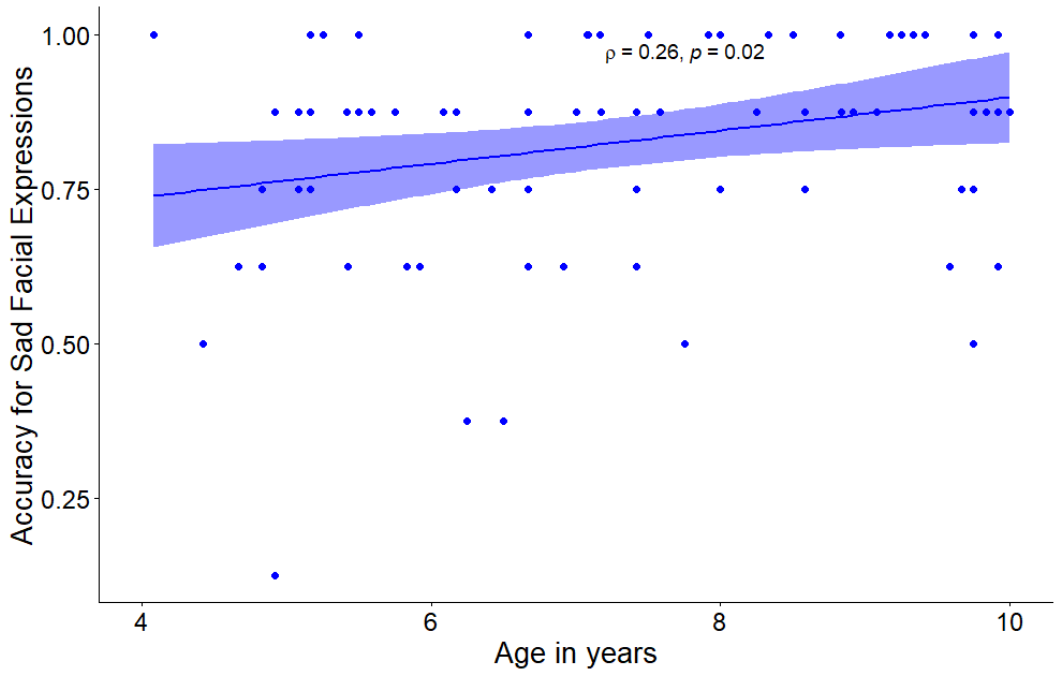

Figure 3.16: The relationship between isolated sad facial expression recognition and age. Each point represents one child. Shaded area represents the 95% confidence interval.

Body Bias and Body Emotion Recognition

Body bias for angry facial expression trials was not significantly correlated with overall isolated body emotion recognition ($\rho = -0.04$, $p = 0.74$; Figure 3.17). On the other hand, the body bias for sad facial expression trials was significantly, and negatively correlated with overall body emotion recognition ($\rho = -0.23$, $p = 0.045$), suggesting that the better children were at recognising isolated body expressions, the less they were influenced by body emotion (Figure 3.18).

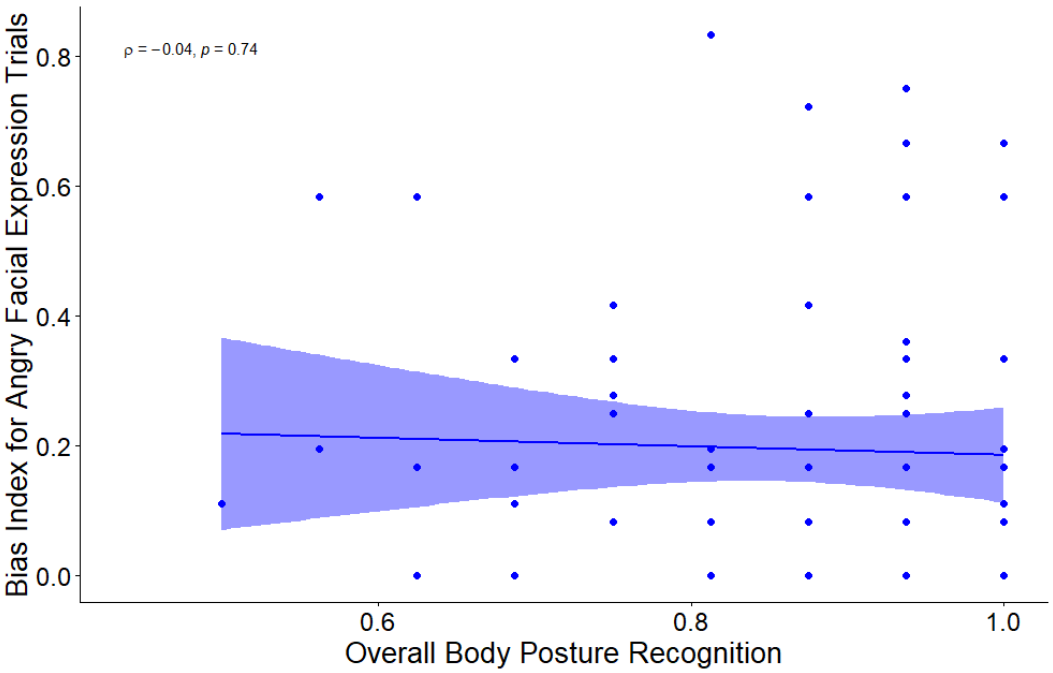

Figure 3.17: Relationship Between Body Bias for Angry Facial Expression Trials and Isolated BER.
Each point represents one child. Shaded area represents the 95% confidence interval.

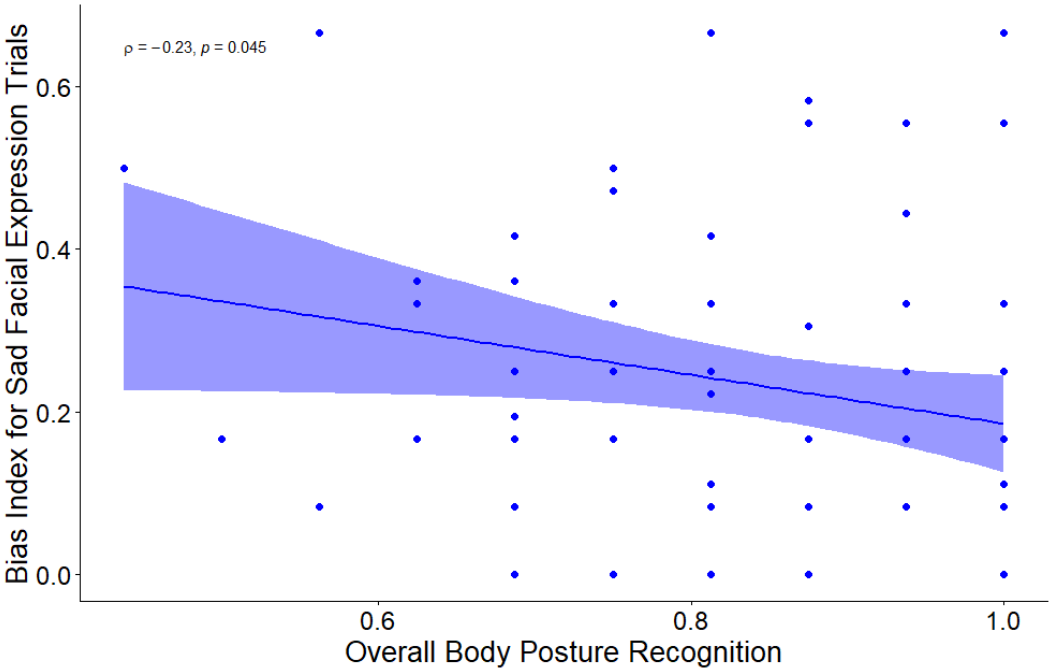

Figure 3.18: Relationship Between Body Bias for Sad Facial Expression Trials and Isolated BER.
Each point represents one child. Shaded area represents the 95% confidence interval.

3.4 Discussion

Contextual cues are integral to shaping our interpretation of facial expressions. The interplay between contextual cues and facial expression recognition underscores the need to further explore this dynamic. In this chapter, I investigated the influence of contextual cues on facial expression recognition in typically developing children. Body expression was found to significantly influence facial expression recognition judgements of children. Specifically, the inclusion of congruent body expressions improved children's angry facial expression recognition performance relative to their accuracy in recognising isolated angry facial expression stimuli. However, incongruent body expressions led to a significant decrease in children's facial expression recognition accuracy. Specifically, their facial expression judgements were biased towards the body emotion during incongruent trials. Furthermore, isolated facial expression recognition ability was identified as a potential underlying mechanism for elucidating the degree to which contextual cues influence facial expression recognition, particularly for angry expressions.

The reduction in facial expression recognition performance during incongruent trials, as compared with congruent trials, aligns with prior research findings (Mondloch 2012; Mondloch, Horner, & Mian 2013; Karaaslan et al. 2020). Notably, the current study distinguishes itself from the work of Mondloch (2012) and Mondloch, Horner, & Mian (2013) by offering empirical support for enhanced performance when congruent body expressions are present in contrast to isolated angry facial expression trials. It is worth noting that Karaaslan, Durmuş, & Amado (2020) compared performance for isolated facial expressions with performance on congruent face-body emotion trials within a young adult sample. They detected higher accuracy in facial expression recognition in congruent trials than in incongruent and isolated facial expression trials. Consequently, the current study contributes to the existing literature by showing that children's angry facial expression recognition improves in the presence of congruent body expressions. The pattern of results was somewhat different for sad facial expressions, suggesting that the interplay between contextual cues and facial expression

recognition can vary depending on the emotional expression under consideration. In the case of sad facial expressions, children's performance was similarly influenced by incongruent body expressions, resulting in lower accuracy than when a congruent body expression or isolated sad facial expression was presented. Surprisingly, however, the presence of congruent sad body expressions did not significantly improve their performance compared with the recognition of isolated sad facial expressions. This may reflect the difficulty in accurately recognising sad body expressions, which were the least well-recognised body emotion in this sample. When children do make errors in incongruent face-body trials however, they are biased towards body emotion in making their judgement of the facial expression. This was consistent across both angry and sad facial expressions. These results align with the existing evidence in the literature that both adults and children are biased towards the emotion conveyed by body expression (Aviezer et al. 2012; Mondloch, Nelson, & Horner 2013; Mondloch 2012).

Delving into the mechanisms governing the influence of body expression on facial expression recognition, I found that children's inclination to label facial expressions as the corresponding body emotion was negatively related to their accuracy in recognising isolated angry facial expressions. In simple terms, as children's ability to recognise isolated angry facial expressions increased, their susceptibility to the influence of accompanying body expressions decreased. This finding is consistent with previous research in children, which found that the precision of facial expression representations increased with age, together with a decrease in the influence of body context with age (Ward et al. 2023). The current study further supports this developmental trend by focusing on children aged 4 to 10, differing from Ward et al. (2023), which examined children aged 8 to 18. This observation suggests that the reliability of facial expression representation might determine the weight it is given in the whole-person percept and is consistent with models of low-level visual processing where each cue's reliability governs its contribution to the integrated percept (Ernst & Banks 2002; Martin 2006). More simply, it is expected that people would rely more on the cues they have more information on their final judgement of facial expressions. Although the current study does not have measures of

precision of facial expression representations, only accuracy of facial expression recognition, the results are consistent with this general idea. Interestingly, a similar relationship between facial expression recognition and the influence of body expression was not observed for sad facial expressions, indicating a divergence in body bias and facial expression recognition between anger and sadness. This disparity could be attributed to age-related differences in the recognition of the respective facial expressions. When controlling for age, the relationship between isolated sad facial expression recognition and the influence of body expression trends towards a negative correlation. Unlike isolated angry facial expression recognition, which shows only a trend with age, isolated sad facial expression recognition is positively and significantly associated with age. The varying impact of age on the recognition of isolated facial expressions for anger and sadness implies that developmental factors exert differential influences on emotional processing, contributing to observed differences in recognition patterns in children. Therefore, the absence of a significant association for isolated sad facial expression recognition and the influence of body expression for sad facial expression trials may potentially be explained by developmental differences for this particular emotion category.

Unexpectedly, an inverse relationship was identified between accuracy in recognising isolated overall body emotion and the predisposition for body bias influencing sad facial expression trials. The reason for this relationship is unclear. However, no such relationship was observed between body bias and overall body emotion recognition in angry facial expressions.

It is noteworthy mention that the relationship between facial expression recognition accuracy and age was only a trend, representing a relatively small link. The literature has well-established that children improve their facial emotion recognition abilities with age Dalrymple et al. 2017; Widen & Russell 2008; Rodger et al. 2015.

While previous studies of emotion recognition have mainly focused on isolated facial expressions, there has been some research on the recognition of isolated body expressions which has led to a growing recognition of the importance of contextual cues such as bodily expressions (Coulson 2004; de Gelder et al. 2006; Pitterman & Nowicki 2017; Martin-Key et al. 2021).

Previous studies on recognition of body expression development have however focused on narrower age ranges, e.g., 3 to 5 years old (N. L. Nelson & Russell 2011), 2 to 4 years old (Wu et al. 2022), or adolescents aged 8-15 years (García-Guerrero et al. 2022). By contrast, the current study explores a wider age range of a younger sample of 4-10-year-old children and showed a significant developmental trajectory for the recognition of body emotion, with improved accuracy with age. Additionally, sad body postures are the least well recognised body emotion across this age group. Overall, therefore, another significant contribution of this chapter is to expand on our understanding of the typical development of body expression recognition in children.

3.4.1 Strength and Limitations

This study has several notable strengths that contribute to its robustness and comprehensiveness. First, it extends its investigation beyond the emotion categories used in previous research (Leitzke & Pollak 2016; Mondloch 2012; Mondloch, Horner, & Mian 2013; Ward et al. 2023), encompassing a broader spectrum of emotional expressions. Leitzke & Pollak 2016 included anger, and disgust facial and body expressions. Whereas Mondloch (2012) and Mondloch, Horner, & Mian (2013) assessed sadness-fear and sadness-happiness face and body pairs. The current study included bodily expressions of anger, happiness, sadness, and fear with both angry and sad facial expressions. The inclusion of multiple, different body emotion categories allows for a broader understanding of how different emotions interact as contextual cues during facial expression recognition. Second, the study delves into isolated body emotion recognition in children, a facet that has received relatively limited attention in previous research. By exploring this dimension, the study not only addresses a critical gap in the literature but also provides valuable insights into how children process emotional signals conveyed by bodily cues independently of facial expressions. In addition, the inclusivity of the study's approach merits facial expression recognition. Rather than excluding participants with lower levels of performance (e.g., Mondloch 2012; Mondloch, Nelson, &

Horner 2013; Mondloch, Horner, & Mian 2013), the study encompasses children with varying degrees of proficiency in facial expression recognition. This variability allowed us to study the relationship between the influence of body expression and facial expression recognition.

In addition to these strengths, some limitations are worth acknowledging in the context of this study. Despite the breadth of face-body emotion combinations, the current study's focus on anger and sadness as facial expressions in the presence of bodily expressions under investigation somewhat restricts the generalisability of the findings. Further research would benefit from the inclusion of broader facial expression categories to explore the influence of context on facial expression recognition. A further potential limitation was the use of adult facial and bodily expression stimuli, instead of child faces and bodies. The current literature suggests that children are better at recognising children's faces than adults' faces, which is known as the 'own-age bias' (Hills & Lewis 2011; Hauschild et al. 2020). Finally, previous studies explored whether children's attention span contributes to lower accuracy in incongruent trials compared with congruent trials. The findings indicated that children, unlike previously assumed, possess the capacity to focus on facial expressions despite the presence of distracting body cues, showing a congruency effect similar to adults (Leitzke & Pollak 2016; Mondloch, Horner, & Mian 2013). However, this study lacks objective measures to assess the impact of attention span on children's performance. Future research would benefit from the inclusion of attention tasks to rule out the limited attention capacity hypothesis. Additionally, the nature of the study being online necessarily meant that no attention checks were carried out during the tasks.

The current findings shed light on the intricate relationships between facial and body emotion recognition and provide insights into the differential impact of context on different facial expressions in children. These results contribute to our understanding of the developmental processes underlying emotion perception and the influence of contextual cues on facial expression processing.

3.5 Conclusion

In conclusion, this chapter provides insights into how contextual cues play a significant role in shaping facial expression recognition in typically developing children. These findings contribute to a broader understanding of the integration of contextual cues involved in emotion recognition, and the principles underlying the influence of contextual cues. The next chapter investigates whether similar principles underlie the integration of facial and bodily cues in an at-risk sample of children with emotional and behavioural difficulties.

Chapter 4

Facial Expression Recognition in Context: An At-risk Sample

4.1 Introduction

Emotion recognition is a crucial tool for evaluating emotional development in various neurodevelopmental conditions. Difficulties in facial expression recognition can lead to impaired prosocial abilities, aggression, and deficits in social cognitive functioning. Impairments in facial expression recognition are evident in conditions like autism, ADHD, mood disorders, and CD (Parker et al. 2013; Wells et al. 2020a; Guyer et al. 2007; Oerlemans et al. 2014; Cooper et al. 2020; Martin-Key et al. 2021; Staff et al. 2021; Wieckowski et al. 2020).

4.1.1 Facial Expression Recognition in Context and Neurodevelopmental Conditions

Recognising and addressing the unique challenges faced by children with emotional and behavioural difficulties is vital for understanding and supporting their social and emotional development (Maynard et al. 2011; Chan & Leung 2022; Roccella & Vetri 2021). According

to recent research, children with autism struggle to recognise emotions from facial expressions (Chaidi et al. 2020; Shanok et al. 2019; Stagg et al. 2021; Wieckowski et al. 2020). Similarly, children with CD were found to struggle with facial expression recognition tasks, especially for negative emotions such as fear, and sadness (Fairchild et al. 2009; Martin-Key et al. 2018).

While most research on emotion recognition has focused on isolated facial expressions, in everyday life these cues are typically encountered together. Exploring the role of contextual cues like body posture in facial expression processing is therefore crucial in order to fully understand emotion recognition difficulties. Nevertheless, limited studies have explored the role of body posture on facial expression recognition in children who deviate from typical emotional and behavioural development. Santamaría-García et al. (2019) found that both adolescent offenders and non-offenders were influenced by body context, with offenders exhibiting greater influence of body context on facial expression recognition compared to non-offenders, especially during incongruent trials. Likewise, Pino et al. (2019) observed that male adolescent offenders showed greater difficulties in facial expression recognition, especially with mismatched facial and body expressions, compared with non-offenders. These studies highlight differences in how body context influences facial expression recognition in children with behavioural difficulties compared with typically developing peers as well as their categorisation tendency towards body context. However, these studies did not address potential underlying mechanisms behind the influence of body context.

In a recent study in adults with autism, Brewer, Biotti, Bird, & Cook (2017) found that both autistic and non-autistic individuals were significantly biased towards body posture during their facial expression judgements but found no differences between groups in the extent of this biasing influence. However, more recent work by Finn et al. (in prep), using a much larger sample, found a significantly reduced biasing influence of body posture on facial expression perception in autistic adults compared to a non-autistic comparison group. Additionally, they found that the extent of the body bias was related to individual differences in the precision of facial expression representations, such that more precise facial expression

representations led to a lower biasing influence of body context. This suggests that, in adults with a neurodevelopmental disorder, there is a similar underlying mechanism guiding the influence of body posture on facial expression perception to that observed in typical development (Chapter 3, Ward et al. 2023).

4.1.2 A Transdiagnostic Approach to Facial Expression Recognition in Context

There is evidence that behavioural difficulties, such as facial expression recognition, associated with particular diagnostic categories, exist on a continuum rather than being categorically present or absent. (da Silva Ferreira et al. 2014; Golan et al. 2015; Pelc et al. 2006). In light of this, recent research has shifted its focus towards a dimensional understanding of these difficulties instead of the traditional categorical approach based on DSM/ICD diagnostic criteria. A categorical approach falls short in considering co-occurrence across psychopathologies, resulting in heterogeneity across samples or excluding individuals who do not meet specific criteria. Transdiagnostic approaches such as the RDoC, adopt a dimensional framework, characterising dimensions to identify common mechanisms underpinning shared behavioural difficulties across diagnoses. (Fusar-Poli et al. 2019; Insel et al. 2010; Stanton et al. 2020). By exploring shared characteristics across a spectrum, transdiagnostic approaches may offer deeper insights into the underlying mechanisms involved in facial expression processing difficulties.

Previous studies that have adopted a transdiagnostic dimensional approach have found that children at-risk, who exhibit emotional and behavioural difficulties but don't have a diagnosis, exhibit shared difficulties in recognising facial expressions (Hunnikin et al. 2020; Wells et al. 2020b; Wells et al. 2020a; Burley et al. 2022). However, it is unclear whether these shared difficulties extend to the recognition of other emotion cues like body posture, and how contextual cues influence the perception of facial expressions in such an at-risk sample. The current study extends this research by adopting an RDoC-informed approach to

understand the influence of contextual cues like body posture on facial expression recognition. By studying children with a range of emotional and behavioural difficulties, without meeting specific diagnostic criteria, this study delves deeply into facial expression recognition and contextual influences across various difficulties. This broader approach has the potential to offer more insight than studies solely focusing on specific diagnostic categories (Millman 2020; Strikwerda-Brown et al. 2019).

4.1.3 The Current Study

The aim of the current study was to investigate emotion recognition skills from facial and bodily cues in a transdiagnostic sample of children with emerging emotional and behavioural difficulties, and to determine how body context influences the perception of facial expressions in these children. In particular, the current study aims to explore the underlying mechanisms of the influence of body context on facial expression recognition in this transdiagnostic sample.

4.2 Methods

4.2.1 Participants

The study comprised a unique sample of 163 (40 female) young children aged 4-8 (M = 6.51, SD = 1.04) from the NDAU sample (as explained in Chapter 3) These children were referred by their teachers to the NDAU due to their behavioural and emotional difficulties. The NDAU sample, following the referral, went through a broad assessment of cognitive, social, and emotional domains that covers various aspects of functioning and well-being, however, as previously explained, they did not have any mental health diagnosis at the time of the assessment. Additionally, the study included 21 (11 female) typically developing children aged 4-8 (M = 6.01, SD = 1.32) recruited from a local community in South Wales. Recruitment for typically developing children occurred via social media, and university platforms e.g., Yammer, and CUBRIC weekly email newsletter. Due to the key difference in the delivery

of the tasks, online vs. in-person, the sample from the previous chapter was not used as a control group. This difference was considered significant enough to potentially influence the results, and therefore, the two samples were not compared directly. Written consent from the parents and verbal consent from the children were obtained. They were given £10 gift voucher as a thank you for their participation. This study was approved by the Cardiff University School of Psychology Research Ethics Committee.

4.2.2 Materials

Behavioural Measures

The same behavioural measures of demographics and SDQ were used as in Section 1.2.2 of Chapter 3, with the only difference being that these measures were obtained in person.

Emotion Recognition Tasks

Emotion recognition tasks included isolated FER, isolated BER, and WPER. The stimuli used and the tasks' structure was as described in Chapter 3, however with some notable exceptions. First, all data for the current study was collected in person. For the NDAU sample, the stimulus presentation occurred via Tobii Studio for the FER and via PsychoPy for the BER and WPER. All tasks occurred via PsychoPy for the TD sample. The order of the tasks was FER, BER, and WPER for the NDAU whereas FER and BER were randomized and WPER was the last task for the Typically Developing (TD) sample. For the NDAU sample, the FER task lacked the narrative of collecting treasure chests through the task.

TD group included 21 children for each task whereas there were 160 children in FER, 144 for the BER, and 134 for the WPER task.

4.2.3 Procedure

Children who attended the NDAU completed the tasks, as part of a larger battery of tasks administered over the course of two visits. Typically developing children were invited to the CUBRIC, and the tasks were completed on a computer, in the presence of a trained researcher.

For both groups, the researchers sat with the child during the tasks but did not suggest any particular responses. The presentation order of the FER and BER tasks was randomised for TD children, whereas in NDAU sample they completed FER first, followed by the BER task. In both groups, the WPER was always the last task, to ensure that all children had had equal exposure to the facial and bodily expressions of emotion before completing the WPER task. Additionally, parents or guardians filled out a range of questionnaires, including the SDQ.

4.2.4 Data Analysis

Data analysis was completed as explained in the Methods Chapter 3.

4.3 Results

4.3.1 Demographics and Behavioural Data

Demographic information is detailed in Table 4.1. There were no statistically significant differences in age between the NDAU and TD groups; U=2067.5, p = 0.12). However, a chi-square test of independence showed that there was a significant difference in gender between the groups, χ^2 (1, N=183) = 7.09, p=0.008, with more females in the TD group. The SDQ, to assess behavioural and emotional difficulties, revealed that the NDAU group exhibited significantly higher difficulties than the TD group across all SDQ subscales, as well as in the overall SDQ scores. Specifically, 79% of the NDAU children exceeded the

cut-off score of 17 or higher, indicating high or very high levels of significant behavioural and emotional problems, as established in a UK norm-based study (Meltzer et al. 2003; https://www.sdqinfo.org/). In contrast, only 0.14% of the TD group surpassed this threshold, underscoring the significantly elevated levels of difficulties within the NDAU group.

Variables	NDAU (N=163) Mean (SD)	TD (N=21) Mean (SD)	Overall (N=184) Mean (SD)	p-value
Age (years)	6.51 (1.04)	6.01 (1.35)	6.45 (1.09)	.12
Gender (% Female)	40 (24.5%)	11 (52.4%)	51 (27.7%)	**<0.05**
Conduct Problems	4.90 (2.58)	2.29 (0.717)	4.59 (2.58)	**<0.001**
Hyperactivity Problems	8.56 (1.98)	4.20 (1.99)	8.07 (2.41)	**<0.001**
Emotional Problems	4.88 (2.72)	1.76 (2.14)	4.52 (2.84)	**<0.001**
Peer Problems	3.62 (2.31)	4.76 (1.09)	3.75 (2.23)	**<0.05**
Prosocial	6.17 (2.54)	8.38 (1.47)	6.43 (2.54)	**<0.001**
Total SDQ	22.0 (6.16)	12.8 (4.17)	20.9 (6.64)	**<0.001**
Internalizing Problems	8.50 (4.22)	6.52 (2.86)	8.27 (4.13)	**<0.05**
Externalizing Problems	13.5 (3.79)	6.29 (2.55)	12.6 (4.33)	**<0.001**

Table 4.1: Descriptive Statistics of Demographics and Behavioural Measures.
The demographics and behavioural data summary of each group were shown with mean and standard deviation values. The differences of the groups for each variable were analysed using the Mann-Whitney test for continuous variables and chi-square for a categorical variable (gender). SDQ = Strengths & Difficulties Questionnaire.

4.3.2 Isolated Emotion Recognition

Isolated Facial Expression Recognition

Overall facial expression recognition performance between the groups showed a significant difference, with the NDAU group performing significantly worse than the TD group, Mann-Whitney U = 795.5, $p < 0.001$ (Section 4.3.2).

A 2 (group) by 4 (emotion category) mixed-ANOVA was run to detect differences in facial expression recognition accuracy between groups and emotion categories. Mauchly's test

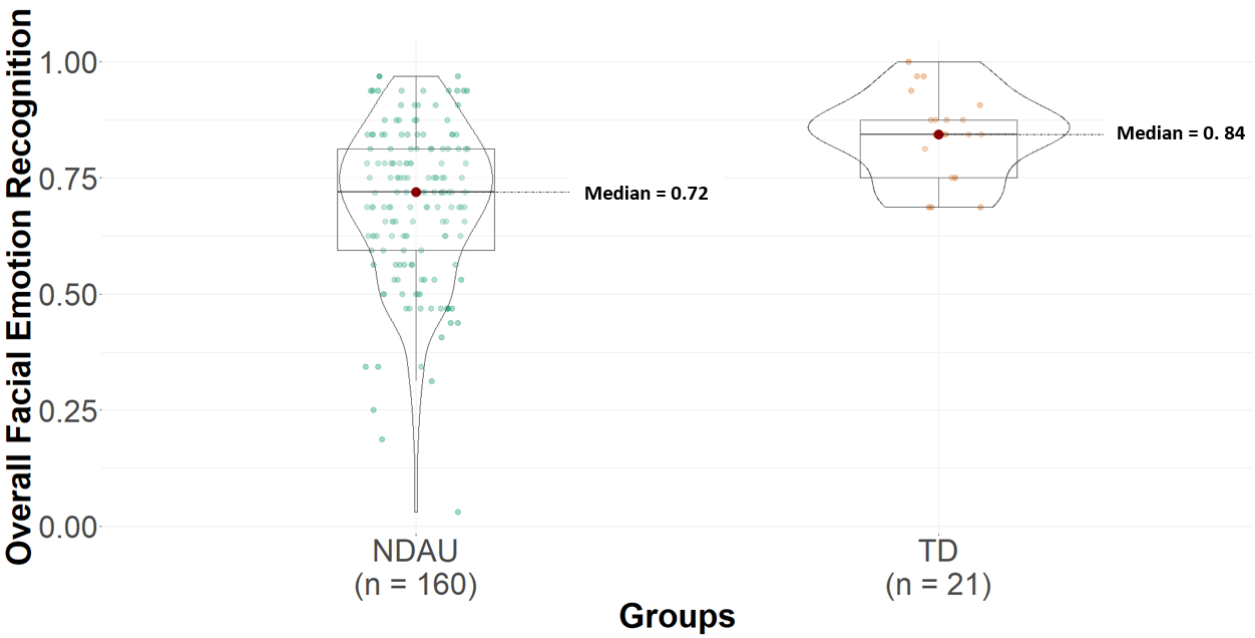

Figure 4.1: Facial Emotion Recognition by group.
The overall facial expression recognition performance of the children in each group is shown on the x-axis, and the accuracy is presented on the y-axis out of 1. The median values and the sample size for each group are presented. Orange represents the TD group, and green represents the NDAU group.

of sphericity was violated, and Greenhouse-Geisser correction was applied. There was a main effect of group ($F = (1, 179) = 15.206$, $p < 0.001$) and emotion categories ($F = (2.724, 487.646) = 27.43$, $p < 0.001$), in addition to a significant interaction of group and emotion categories, ($F = (2.724, 487.646) = 5.948$, $p = 0.002$). Bonferroni-corrected post hoc tests showed that the NDAU group was significantly less accurate in recognising angry facial expressions ($p = 0.001$) and fearful facial expressions ($p < 0.001$) compared with the TD group, whereas the performance for happy ($p = .361$) and sad ($p = .126$) facial expressions did not significantly differ (Figure 4.2).. Within the NDAU group, post hoc analyses demonstrated a notably higher accuracy in identifying happy facial expressions than angry, sad, and fearful facial expressions ($p < 0.001$). Furthermore, the recognition of fearful facial expressions exhibited lower accuracy than both angry facial expressions ($p < 0.001$) and sad facial expressions ($p < .001$) in the NDAU group. In contrast, the TD group displayed no significant differences among facial expression categories.

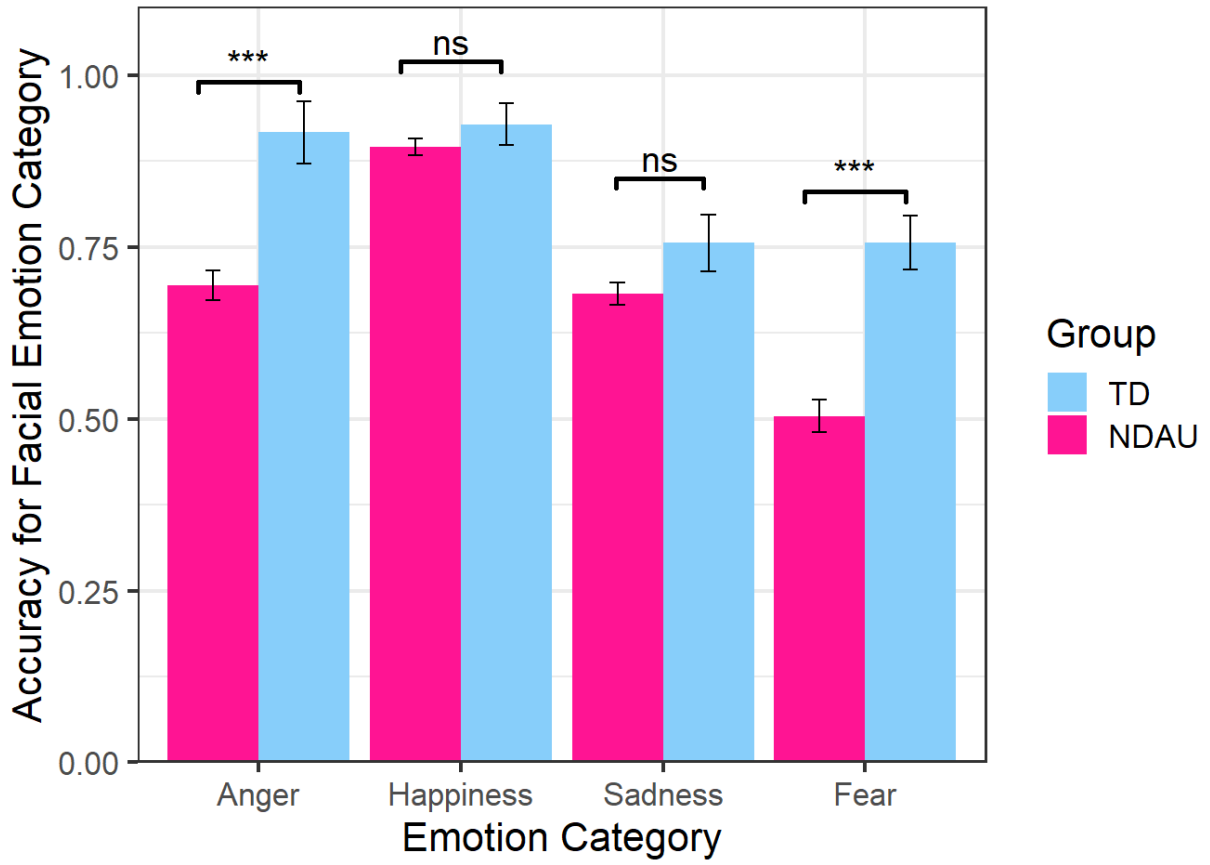

Figure 4.2: Facial Emotion Recognition by emotion categories.
*** indicates significant difference at p $<$ 0.001; ns = non-significant.

Isolated Body Emotion Recognition

Overall body emotion recognition accuracy did not significantly differ between the groups, Mann-Whitney U = 1438, $p = 0.72$ (Figure 4.3). Using Greenhouse-Geisser correction, a 2 (group) x 4 (emotion category) mixed-ANOVA was run to compare the performance for different body emotion categories between the NDAU and TD groups. There was a significant main effect of emotion categories, F (2.818, 459.374) = 23.132, $p < 0.001$. However, there was no significant effect of group, F (1, 163) = 0.816, $p = 0.368$, suggesting largely similar body emotion recognition ability in NDAU and TD children, nor was there an interaction between emotion category and group F (2.818, 459.374) = 1.381, $p = 0.249$ (Figure 4.4). Post hoc tests for emotion categories showed that sad body expressions were most difficult to recognise compared with angry ($p < .001$), happy ($p = 0.023$), and fearful body expressions

($p < 0.001$). Happy body expressions were more difficult to recognise than angry body expressions ($p = 0.003$), and fearful body expressions ($p < 0.001$).

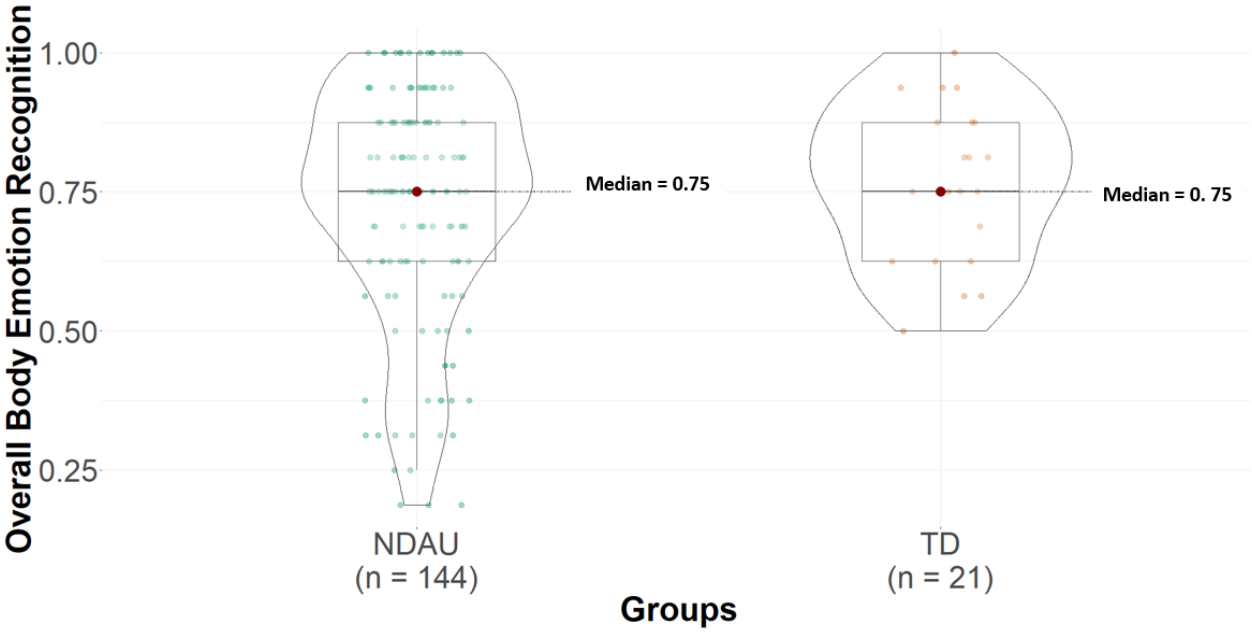

Figure 4.3: Body Emotion Recognition by group.
The overall body emotion recognition performance of children for each group was shown on the x-axis, and the accuracy was presented on the y-axis out of 1. The median values and the sample size for each group were presented. Orange depicts the TD group, and green depicts the NDAU group.

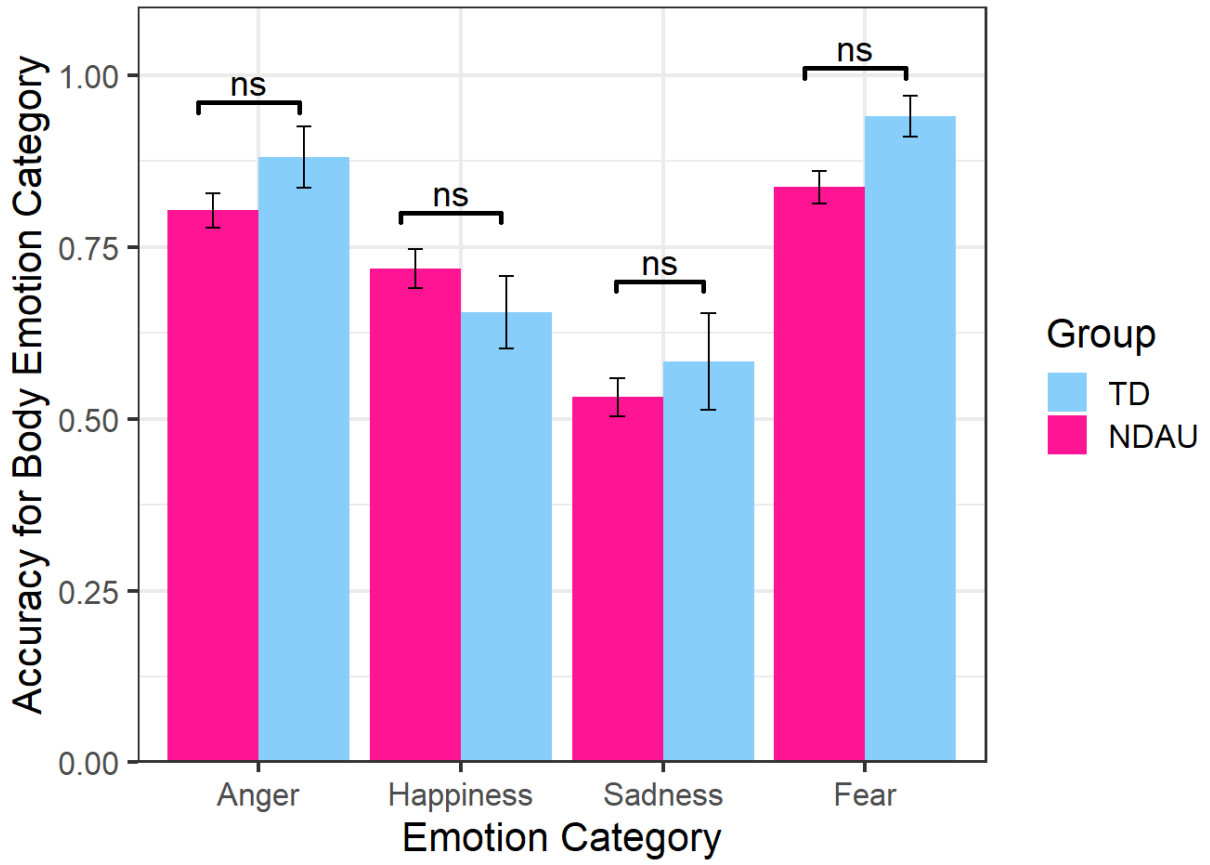

Figure 4.4: Body Emotion Recognition by emotion categories.
ns = non-significant.

4.3.3 Facial Emotion Recognition in the Context

Facial Emotion Recognition Accuracy

To assess the influence of body context on facial expression recognition, a 2 (trial type) x 2 (group) mixed-ANOVA was performed. Here, trial type was the accuracy of facial expression recognition for congruent or incongruent trials in the WPER task. A significant main effect of trial type was detected, F (1, 153) = 155.959, $p < 0.001$, with higher accuracy for congruent trials. There was no effect of group (F (1, 153) = 1.126, $p = 0.290$). There was a borderline interaction between trial type and group (F (1, 153) = 3.163, $p = 0.077$). Bonferroni-corrected post hoc tests revealed that the borderline interaction effect is driven by the trial type difference suggesting that both groups are better at recognising congruent

trials than incongruent trials ($p < .001$), with no difference between each other, p-values of NDAU and TD respectively p=.878, and p=.354. (Figure 4.5).

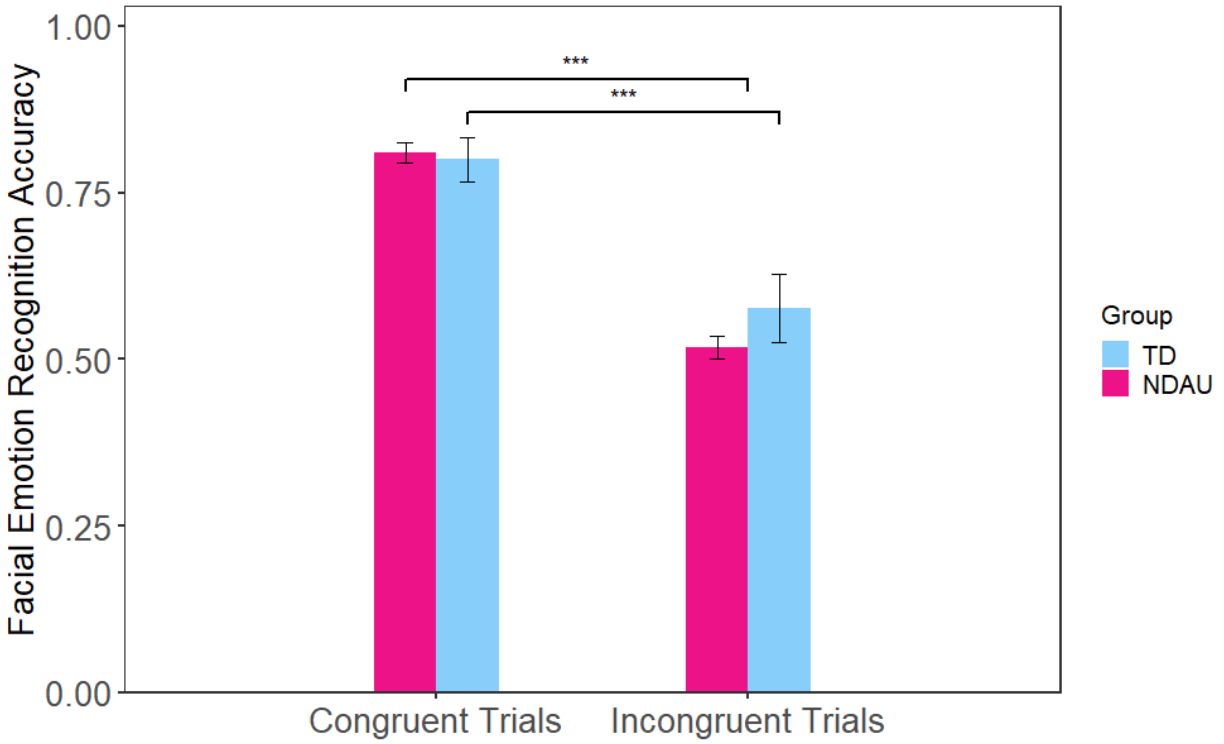

Figure 4.5: The Comparison between the NDAU and TD for the Accuracy in Congruent and Incongruent Trials.
The significant differences ($p < 0.001$) are shown with asterisks (***).

Angry Facial Expressions

To assess whether the addition of a congruent body posture improved anger facial expression recognition relative to isolated facial expressions, a 2 (group) by 3 (trial type: FER, Congruent, and Incongruent) mixed ANOVA with Greenhouse-Geisser correction showed a significant main effect of trial type ($F\ (1.979, 269.18) = 53.702$, $p < 0.001$) and a significant main effect of group ($F\ (1, 136) = 8.334$, $p = 0.005$; Figure 4.6). The interaction between the trial type and group was significant, $F\ (1.979, 269.18) = 2.546$, $p = 0.081$. Bonferroni-corrected post hoc tests showed a significant difference between NDAU and TD children in their isolated angry facial expression recognition ($p < 0.001$), but not for angry facial expression

trials with a congruent body posture ($p = .372$) or for angry facial expressions with an incongruent body posture ($p = 0.44$). Both the NDAU ($p < 0.001$) and TD ($p < 0.001$) groups showed significantly better performance in the isolated facial expression recognition compared with the incongruent angry facial expression trials. The NDAU group showed a significant improvement in facial expression recognition accuracy for the congruent face-body trials relative to the isolated angry facial expression recognition accuracy ($p < 0.001$). Conversely, the TD group did not show a significant improvement for the same comparison ($p = .932$), indicating that only the NDAU group benefited from the addition of a congruent angry emotional body posture.

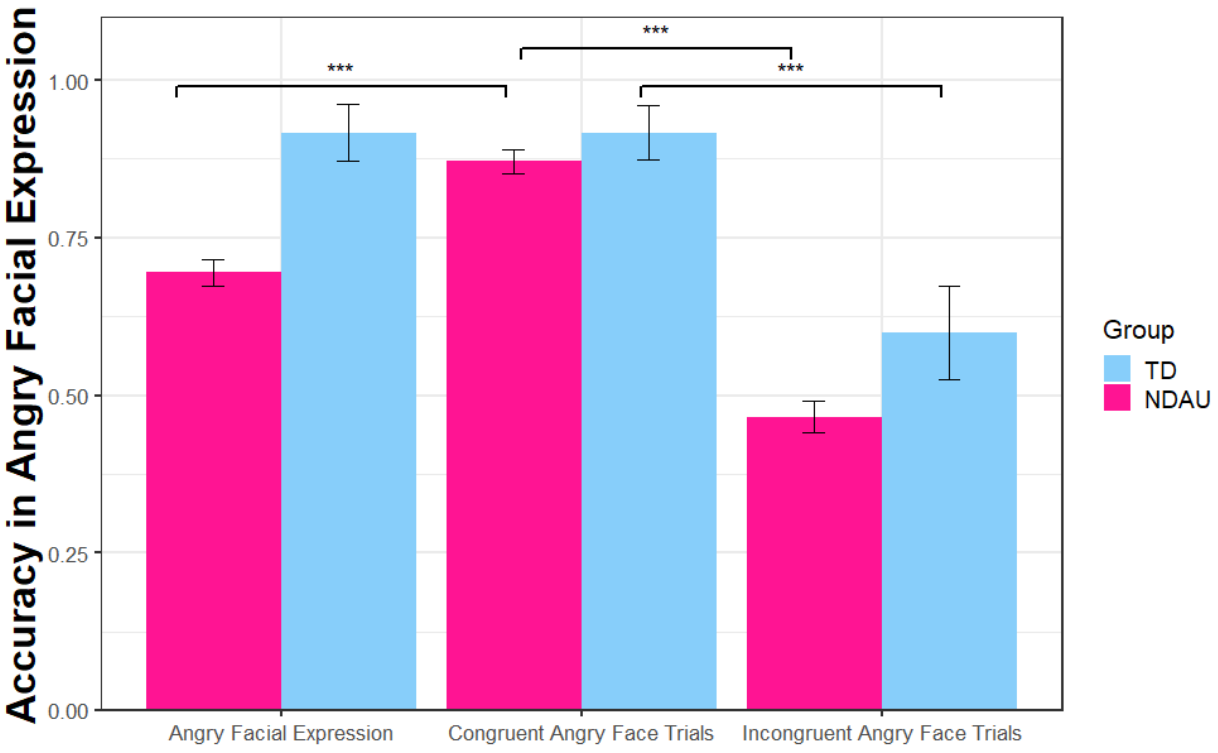

Figure 4.6: The Accuracy Comparison for Isolated FER, Congruent, and Incongruent WPER of Angry Facial Expression Trials.
The significant differences ($p < 0.001$) are shown with asterisks (***).

Sad Facial Expressions

A similar 2 (group) x 3 (trial type) mixed-ANOVA corrected with Greenhouse-Geisser for sad facial expressions showed a significant main effect of trial type (F (1.986, 270.112) = 37.315, $p < 0.001$), but not group (F (1,136) = 0.022, $p = .883$), nor was there an interaction between trial type and group (F (1.986, 270.112) = 1.504, $p = .224$). Bonferroni corrected post hoc tests demonstrated that isolated sad facial expression recognition significantly differed from incongruent trials with sad facial expressions ($p < 0.001$), whereas there was a significant difference between isolated facial expression recognition and congruent trials with sad facial expressions ($p = 0.033$). Furthermore, the congruent trials of sad facial expressions were significantly different from the incongruent trials of sad facial expressions, p<0.001 (Figure 4.7).

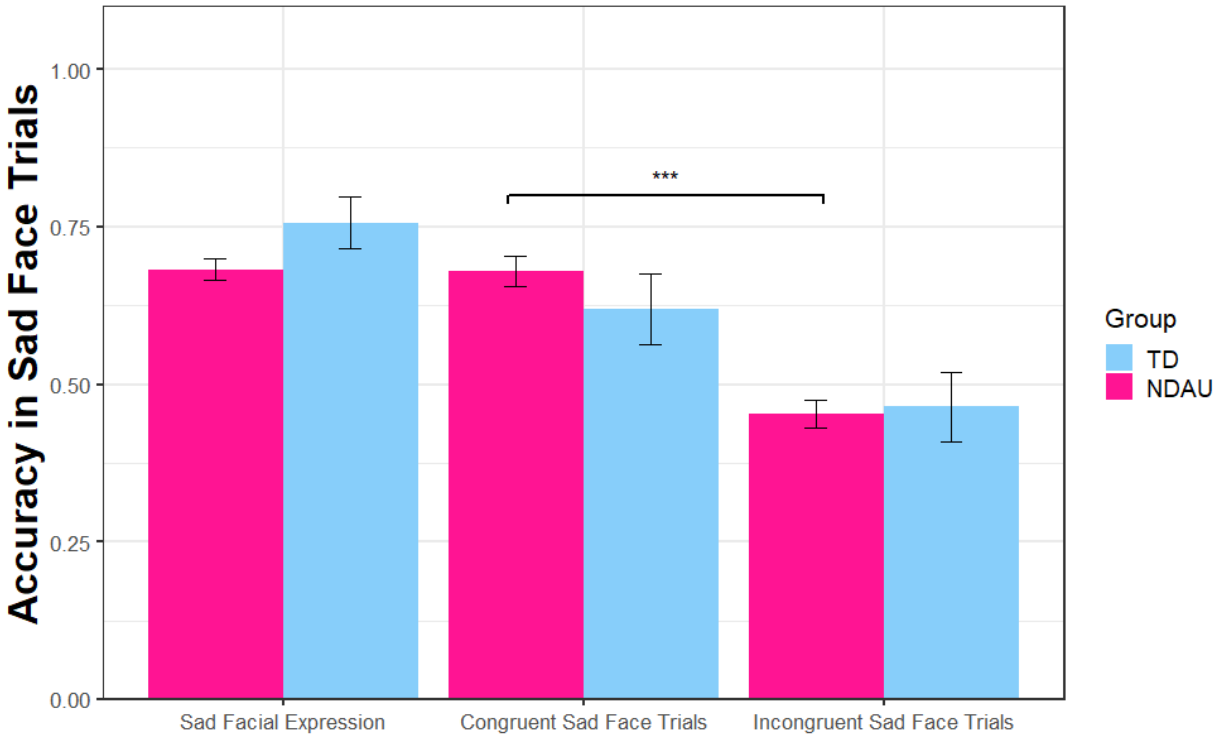

Figure 4.7: The Accuracy Comparison for Isolated FER, Congruent, and Incongruent WPER of Sad Facial Expression Trials.
The significant differences ($p < 0.001$) are shown with asterisks (***).

The following two analyses were run to show the influence of body context on facial emotion

recognition specifically for the angry and sad facial expression trials. Additionally, the accuracy of angry and sad isolated facial emotion recognition performance of the groups was included to demonstrate whether the presence of the congruent body stimuli improves the facial emotion recognition performance.

4.3.4 Biasing Influence of Body Expression on Facial Expression Recognition

While the difference in facial expression accuracy for congruent vs. incongruent trials in both the NDAU and TD groups indicates that body posture has a significant effect on facial expression perception, these results do not address whether there is a shift to respond as the body emotion. In order to address this, the likelihood of labelling a facial expression as the body emotion in incongruent trials (i.e., body emotion) was compared with the likelihood of mislabelling in congruent trials (i.e., all errors).

Angry Facial Expressions

The results indicated no main effect of group, F (1, 153) = 1.895, $p = .171$, indicating that the NDAU and TD children did not show differential response patterns in their bias towards body emotion for angry facial expression trials. However, significant main effects of response type (F (1,153) = 264.117, $p < 0.001$) and of body context (F (1,153) = 56.410, $p < 0.001$) were observed. A significant interaction effect of response type and body context was also found, F (1,153) = 92.275, $p < 0.001$ (Figure 4.8). There was no significant interaction between response type, body context and group, F (1,153) = 1.639, $p = .202$.

Bonferroni-corrected post hoc tests revealed a significant difference in anger responses in congruent trials and incongruent trials ($p < 0.001$), where incongruent body expressions reduced the accuracy of anger facial expression recognition compared with the congruent trials. Likewise, there was a significant difference between the body emotion/other emotion responses in congruent trials compared with responses in incongruent trials ($p < 0.001$), with

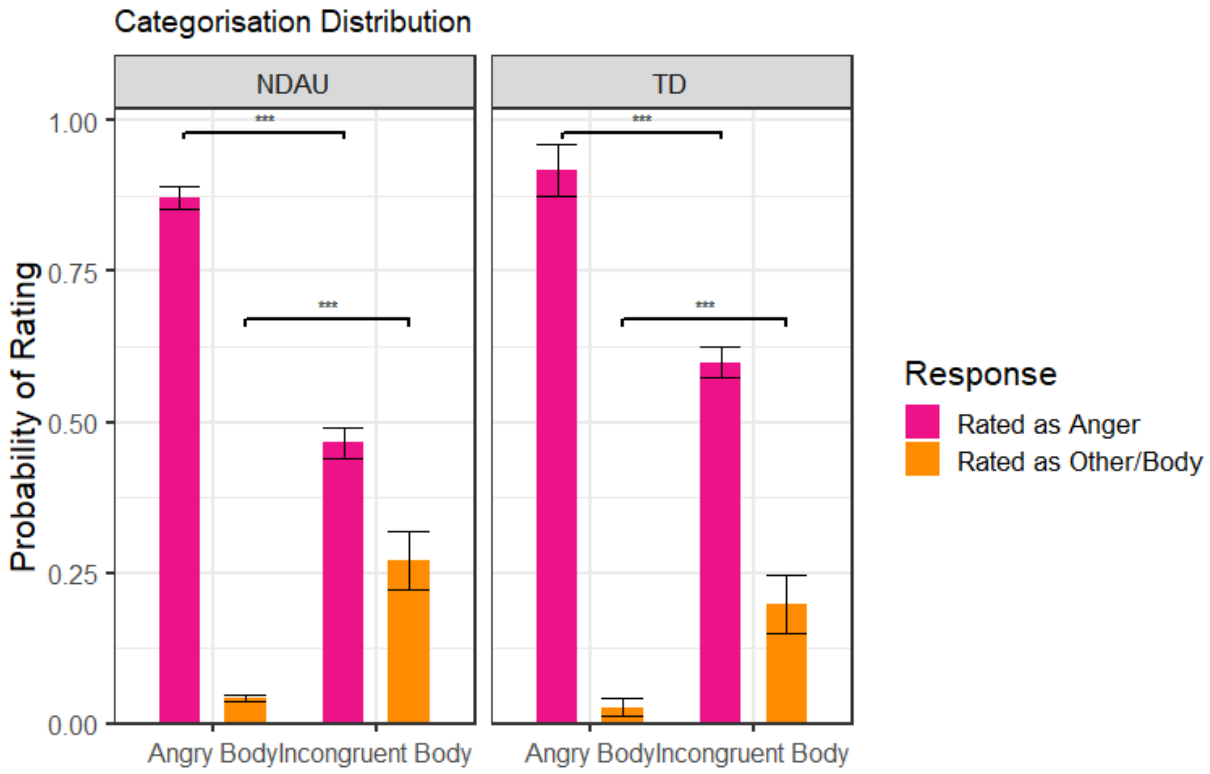

Figure 4.8: The proportion of rating as face and body among angry facial expression trials. The x-axis shows the body context condition, and the y-axis shows the proportion of ratings for anger and other/body emotion. *** identifies $p < 0.001$, according to the Bonferroni-corrected post hoc tests.

a shift towards body emotion in incongruent trials. For both congruent and incongruent trials, there were significantly more anger responses than body emotion/other emotion responses (p's< 0.001).

Sad Facial Expressions

A similar mixed-design ANOVA for sad facial expressions was conducted to detect whether there is a shift to respond as the body emotion. There was no main effect of group, F (1, 153) = 0.098, $p = .754$. However, a significant main effect was observed for body context (F (1, 153) = 74.479, $p < 0.001$), whereas none was detected for response type (F (1, 153) = 2.576, $p = 0.111$). Furthermore, there was a significant interaction between response type and body context, F (1, 153) = 63.067, $p < 0.001$. However, there was no significant interaction

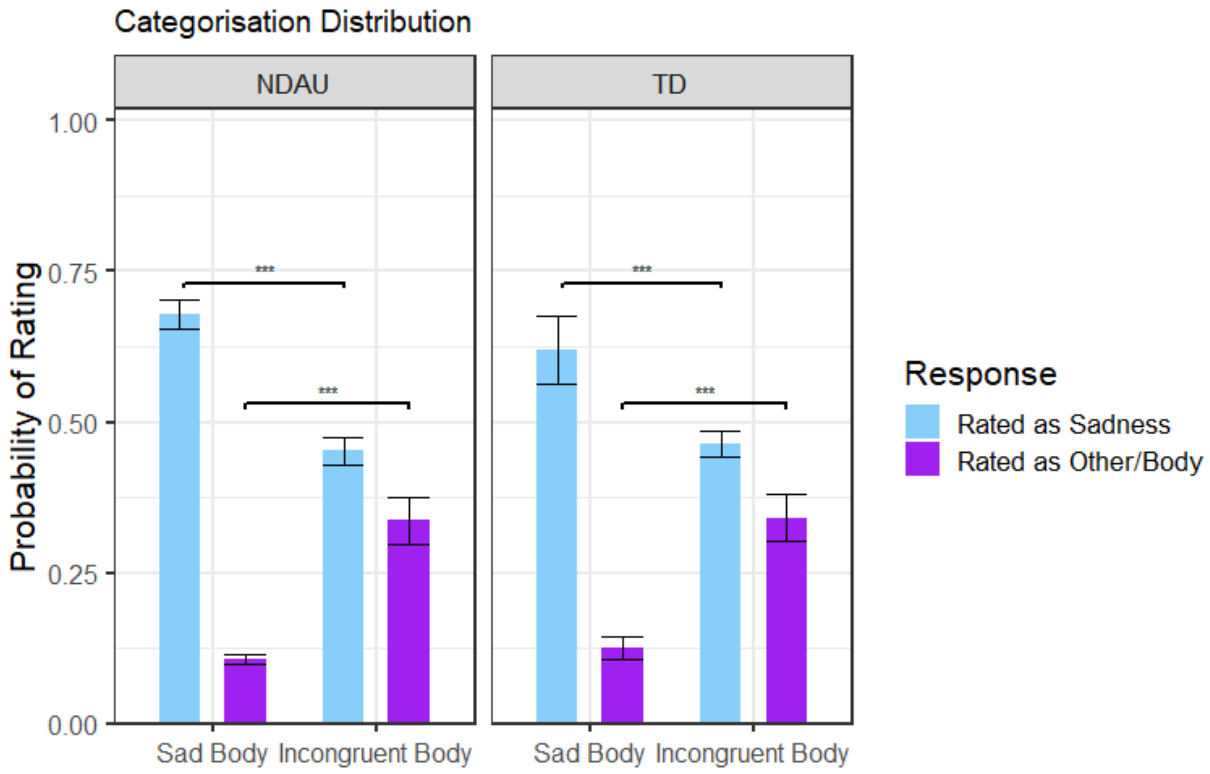

Figure 4.9: The proportion of rating as face and body among sad facial expression trials. The x-axis shows the body context condition, and the y-axis shows the proportion of ratings for sadness and other/body emotion. *** identifies $p < 0.001$, according to the Bonferroni-corrected post hoc tests.

between response type, body context and group, F (1,153) = 0.716, $p = .399$.

A Bonferroni-corrected post hoc analysis demonstrated that sad responses in congruent trials were significantly greater than those in incongruent trials ($p < 0.001$), suggesting that facial expression recognition performance is diminished in the presence of incongruent body expressions. The 'other emotion' responses in congruent trials showed a trend towards a significant difference from body emotion responses in incongruent trials ($p = .059$). Both within congruent ($p < 0.001$) and incongruent trials ($p < 0.001$), there were significantly more sad responses than body emotion/other emotion responses (see Figure 4.9).

Body Bias and Facial Emotion Recognition

To determine whether children's accuracy in isolated facial expression recognition underlies the extent to which the body context influences their facial expression judgements, Spearman rank correlation was performed. Body bias for angry facial expressions showed a significant, negative correlation with isolated angry facial expression recognition accuracy in the NDAU (ρ = -0.28, $p = 0.0024$; controlling for age, ρ = -0.28, $p = 0.0022$), and a trend for negative correlation in the TD (ρ = -0.43, $p = 0.076$; controlling for age, ρ = -0.37, $p = 0.13$) groups, as illustrated in Figure 4.10. The NDAU group exhibited a significant, negative correlation between the body bias index for sad facial expression trials and isolated sad facial expression recognition (ρ = -0.33, $p < 0.001$; controlling for age, ρ = -0.32, $p < 0.001$). However, the TD group did not show a significant correlation for sad facial expressions (ρ = -0.16, $p = 0.52$; controlling for age, ρ = -0.16, $p = 0.52$), as shown in Figure 4.11.

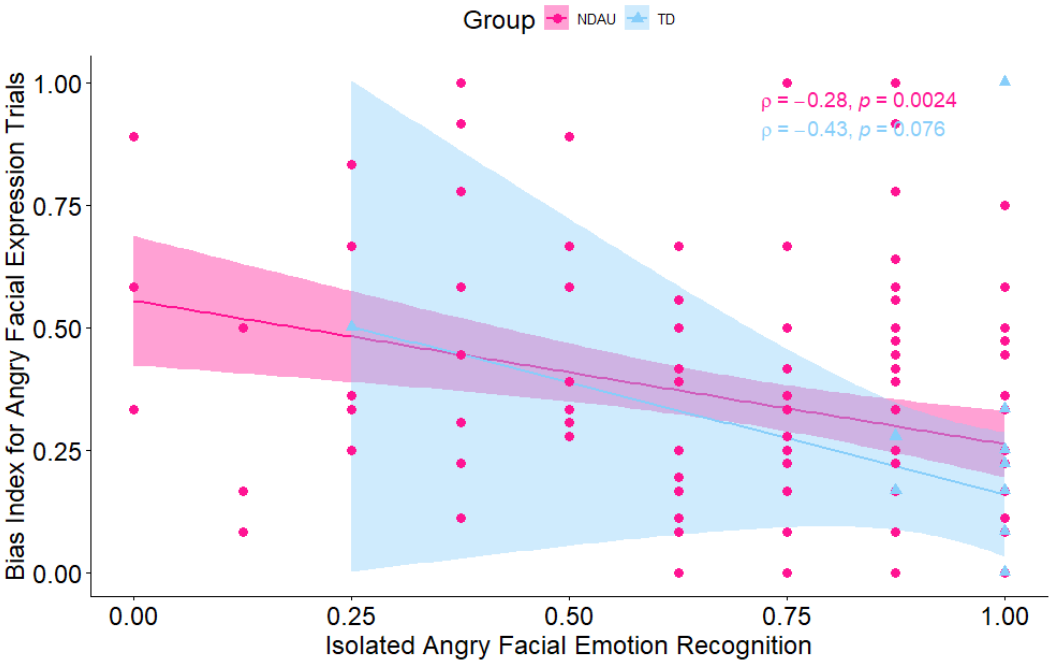

Figure 4.10: The Body Bias Index and Angry Facial Emotion Recognition. Each dot or triangle represents one child. Blue triangles depict the TD group, and pink circles depict the NDAU group. Shaded area represents the 95% confidence interval.

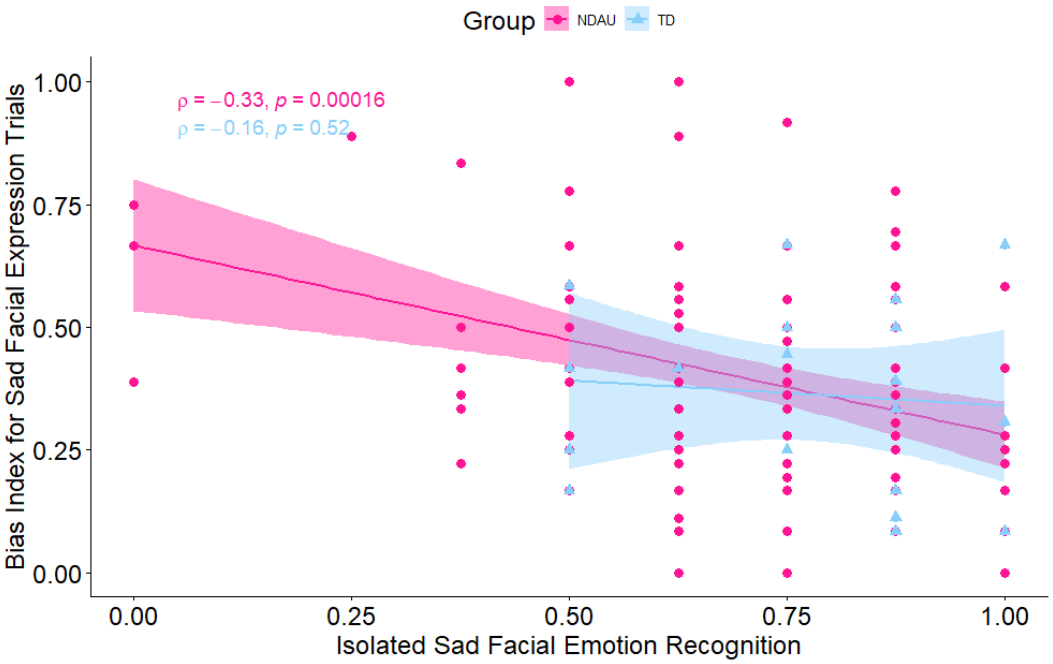

Figure 4.11: The Body Bias Index and Sad Facial Emotion Recognition. Each dot or triangle represents one child. Blue triangles depict the TD group, and pink circles depict the NDAU group. Shaded area represents the 95% confidence interval.

Body Bias and Body Emotion Recognition

To examine whether children's accuracy in isolated overall body emotion recognition is linked to the extent to which they are influenced by the body context, Spearman rank correlation was conducted. The NDAU group did not exhibit any significant correlation between the body bias index for either angry or sad facial expression trials and isolated overall body expression recognition, respectively, ρ = 0.062, p = 0.54 and ρ = -0.05, p = 0.61. Likewise, the TD group did not show a significant correlation for the body bias index of either angry or sad facial expressions, ρ = -0.062, p = .81 and ρ = -0.15, p = .53 as shown in Figure 4.12 andFigure 4.13.

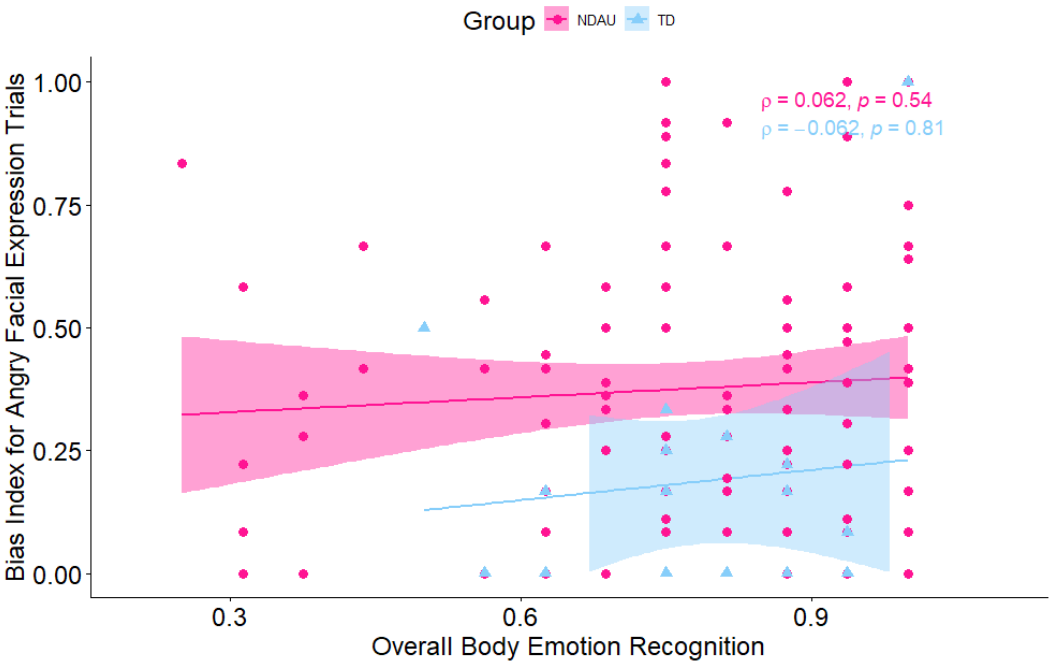

Figure 4.12: The Body Bias Index for Angry Facial Expression Trials and Overall Body Emotion Recognition.
Each dot or triangle represents one child. Blue triangles depict the TD group, and pink circles depict the TD group. The shaded area represents the 95% confidence interval.

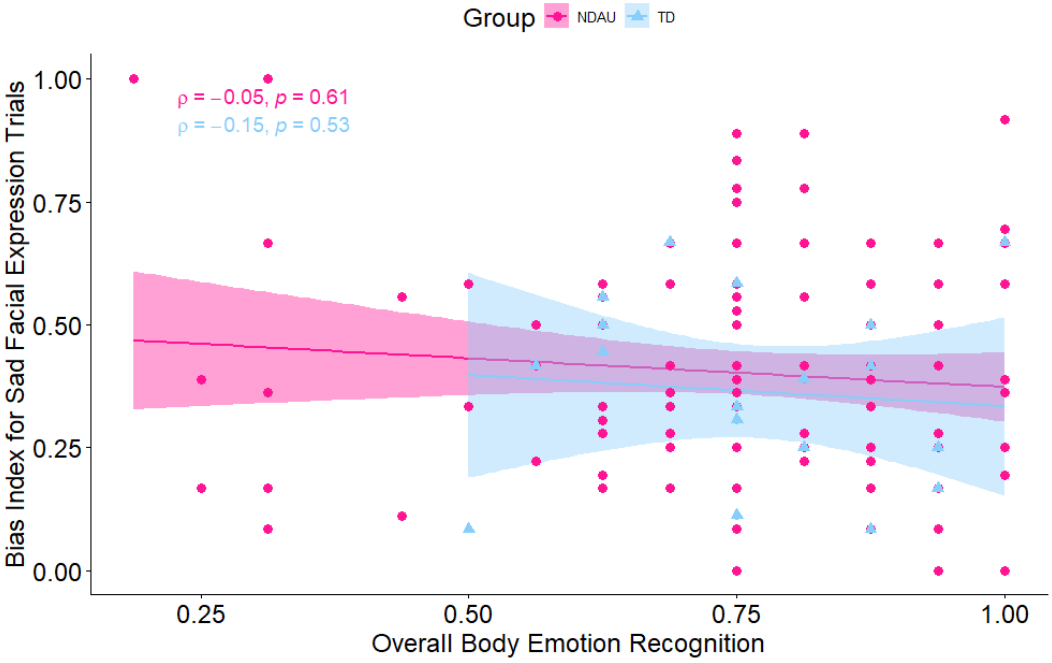

Figure 4.13: The Body Bias Index for Sad Facial Expression Trials and Overall Body Emotion Recognition.
Each dot or triangle represents one child. Blue triangles depict the TD group, and pink circles depict the NDAU group. The shaded area represents the 95% confidence interval.

4.4 Discussion

This investigation explored emotion recognition in a transdiagnostic cohort of children with emotional, cognitive, and/or behavioural difficulties. Notably, these children exhibited difficulties in recognising isolated facial expressions compared with their typically developing peers. However, their ability to recognise isolated body expressions was similar to that of typical children. When making facial expression judgments in the context of a body posture, both groups of children showed reduced accuracy in facial expression recognition when body emotion was incongruent to the facial expression, relative to when it was congruent. Furthermore, the impact of body context on facial expression recognition judgments was associated with children's performance in isolated facial expression recognition, such that worse facial expression recognition accuracy was associated with a larger influence of body posture. Interestingly, for children with emotional and behavioural difficulties, this relationship between the influence of body posture and facial expression recognition was consistent across both angry and sad facial expressions, whereas this association was borderline significant for angry facial expressions, and not obvious for sad facial expressions, in TD children. The latter is consistent with the findings of the preceding chapter, where the isolated facial expression recognition performance of typically developing children did not predict their susceptibility to the influence of body context on sad facial expressions.

Children with emotional, cognitive, and/or behavioural difficulties exhibited notable deficits in isolated facial expression recognition tasks compared with their typically developing peers. This is consistent with previous research on non-diagnosed children with behavioural and emotional problems, indicating their challenges in facial expression recognition relative to typically developing peers (Burley et al. 2022; Wells et al. 2020a; Wells et al. 2020b). Facial expression recognition difficulties are commonly associated with neurodevelopmental conditions such as autism, ADHD, and CD (Collin et al. 2013; Stagg et al. 2021; Peterson et al. 2015). Despite not having a specific diagnosis and displaying a range of characteristics associated with various diagnostic categories, children with emotional and behavioural diffi-

culties exhibited facial expression recognition impairments. The presence of such impairments suggest that facial expression recognition difficulties may be a key indicator of potential future transition to a diagnosed condition in children and is a common characteristic across at-risk children. The difference in facial emotion recognition was found only in the categories of anger and fear. The absence of this difference for happiness may be due to a ceiling effect, where children perform at a high and stable level in recognising happy facial expressions early in development. This has been demonstrated in previous studies, demonstrating that children generally have a strong ability at identifying happiness from an early age Barisnikov et al. 2021; Herba & Phillips 2004. Interestingly, in earlier research, children with autism showed better performance in recognising happiness and sadness compared to anger and surprise, suggesting that at-risk children may have fewer difficulties in recognising happiness and sadness Golan et al. 2018. Additionally, given that the ability to recognise sad facial expressions improves and stabilises after the age of six Lawrence et al. 2015, and the average age of children in this study being around six, this could explain why there was no difference in recognising sadness between children with emotional, cognitive, or behavioural difficulties and their typically developing peers. Interestingly, however, no significant differences were found in isolated body emotion recognition accuracy between the groups. Prior research on neurodevelopmental conditions, particularly autism, has yielded varying results regarding the recognition of body expressions in children. Some studies indicated that autistic children had difficulties in body expression recognition compared with typically developing children (Fridenson-Hayo et al. 2016; Philip et al. 2010), whereas others provided evidence that they did not differ significantly in body expression recognition from typically developing children (Actis-Grosso et al. 2015; Peterson et al. 2015). Overall, the present findings demonstrate the impairment in facial expression recognition within the NDAU group and highlight the relative specificity of facial expression recognition difficulties, rather than a general impairment in emotion recognition that extends to body expressions.

Remarkably, children with emotional, cognitive, and/or behavioural problems showed an

improvement in angry facial expression recognition in the presence of a congruent bodily cue. This suggests that the integration of congruent bodily expressions provided valuable contextual information that significantly facilitated their ability to accurately perceive and interpret angry facial expressions. However, this facilitatory effect was not observed in the case of sad faces with accompanying sad body expressions, where recognition was similar to isolated sad faces. This discrepancy in the congruency advantage between angry and sad facial expressions might be explained by body expression recognition ability, where recognition of isolated sad body expressions was the worst of all body emotions shown. However, it is interesting to speculate that facial expression recognition ability in children with difficulties can be facilitated by providing a well-recognised congruent contextual cue.

Both the children with emotional, cognitive, and/or behavioural problems and typically developing children exhibited better performance in congruent trials than in incongruent trials when recognising facial expressions within a bodily context. This implies that incongruent bodily expressions negatively impacted all children's ability to recognise facial expressions. This observation aligns with the existing literature, which consistently reports a decline in facial expression recognition accuracy in the presence of incongruent body expressions among typically developing children and adults (Aviezer et al. 2008; Aviezer et al. 2012; Mondloch 2012; Mondloch, Horner, & Mian 2013).

Further analysis revealed a bias in children's responses towards emotional expressions conveyed by incongruent bodily cues. These findings support prior research indicating that adults tend to be biased towards the accompanying body expression when judging facial expressions (Aviezer et al. 2008; Aviezer et al. 2012). In the current study, both typical children and those with emotional, cognitive, and/or behavioural difficulties exhibited a perceptual bias towards the presented bodily context when evaluating facial expressions. Furthermore, children with emotional, cognitive, and/or behavioural difficulties showed a clear link between their proficiency in recognising isolated facial expressions and the biasing influence of bodily expressions on their facial expression recognition judgements. This implies that those children

who could discriminate isolated facial expressions more accurately were less biased towards body emotion when making judgements about facial expressions. This is consistent with the findings in Chapter 3 and builds on prior research which showed a decreasing biasing influence of body expressions with age in typically developing children and adolescents, together with improvements in isolated facial expression recognition with age (Ward et al. 2023). Reliability-based cue weighting principles suggest that humans process visual information from multiple cues, where the reliability of each cue determines the relative influence of each of those cues in our final percept (Ernst & Banks 2002). Although the current study does not have measures of the precision of children's emotion signal representations, this framework can be useful in understanding the results found here. In the specific case of facial expression recognition in the context of a body posture, children may assign a greater weight to facial signals of emotion when the representations of these cues are more precise (i.e. they are more accurate in recognising facial expressions). While the TD group here only showed a trend towards a similar relationship, it is important to highlight that TD children exhibited a ceiling effect in isolated facial expression recognition tasks, even for low-intensity facial expressions. Notably, the much larger TD sample in Chapter 3 demonstrated a parallel relationship between the biasing influence of body posture and isolated facial expression recognition ability. This suggests that despite difficulties in facial expression recognition, similar principles appear to govern the biasing influence of body posture on facial expression perception in children with emotional and behavioural difficulties and in typically developing children, where facial expression recognition ability is a significant determinant of the influence of body posture.

4.4.1 Strength and Limitations

To the best of my knowledge, no prior studies have explored emotion recognition difficulties in the presence of contextual cues in an at-risk sample of young children, making the current study particularly unique. The emphasis on at-risk populations aligns with transdiagnostic dimensional approaches and contributes to our understanding of emotion processing in

children at-risk. Notably, the mechanisms governing the influence of body context on FER judgements were found to be consistent across both TD, particularly in the larger sample in Chapter 3, and at-risk children, with isolated FER performance emerging as the primary driver of this influence. Given the current findings in an at-risk sample, it is tempting to speculate that similar mechanisms will guide the integration of emotion signals from face and body across diagnoses that are characterised by facial expression recognition difficulties. However, future research is needed to address this directly.

It is important to acknowledge several limitations inherent in this study. First, the sample size of typically developing children was relatively small. The modest number of participants in this group raises the concern that the findings may lack generalisability, given the potential for limited statistical power. Nevertheless, despite the modest size of the control group, the study managed to identify comparable underlying mechanisms in both the typically developing and at-risk groups, aligning with the evidence presented in the previous chapter involving typically developing children. However, future work could explore combining and comparing the online sample from the previous chapter with the NDAU sample from the current chapter. Second, as mentioned in Chapter 3, the current study used adult facial expressions and body postures as stimuli. The own-age effect refers to the ability to perform better in recognising and detecting the facial expressions of peers than non-peers. Children show better performance in recognition tasks when child faces are presented compared with adult faces in both typically developing and at-risk samples (Hills & Lewis 2011; Hauschild et al. 2020; Zsido et al. 2021). However, although using own-age faces and bodies might improve recognition performance, there is no reason to believe that this would fundamentally alter the mechanisms by which body context exerts an influence on facial expression recognition. Additionally, the selection of exclusively angry and sad facial expressions for the whole-person stimuli, motivated by considerations of children's attention span, warrants recognition. This circumscribed focus overlooks the potential influence of other negative emotions, such as fear, and the manner in which positive emotions, such as happiness, could influence the

findings within both groups. Hence, future investigations would benefit from a broader range of emotional stimuli, to better characterise the integration of emotion signals from face and body.

4.5 Conclusion

In this study, I investigated the ability of children with emotional and behavioural difficulties, as well as typically developing children, to recognise emotions based on isolated facial and body cues, and the influence of body posture on facial expression recognition. The findings revealed that children with emotional, cognitive, and/or behavioural difficulties performed worse than typically developing children in recognising isolated emotions from facial expressions. However, their recognition of emotion from isolated body postures was unimpaired. Furthermore, the children's ability to recognise isolated facial expressions predicted the biasing influence of body emotion on their judgements of facial expressions, and this influence showed a similar pattern in both groups of children. This effect was evident for both angry and sad facial expressions in children with emotional, cognitive, and/or behavioural difficulties, indicating that the mechanisms underpinning the bias towards body emotion are not specific to one emotional category. The results suggest that, despite difficulties in emotion recognition in a transdiagnostic sample of children with emotional, cognitive, and/or behavioural difficulties, the integration of emotion signals from the face and body appears to be governed by principles similar to those in typically developing children.

Chapter 5

Structural Markers of Facial Expression Recognition in Children

5.1 Introduction

Recognition of facial expressions plays a crucial role in comprehending social cues within the context of interpersonal interactions. As described in Chapter 4, impairments in facial expression recognition are a key shared characteristic observed across neurodevelopmental diagnoses (Chaidi et al. 2020; Shanok et al. 2019; Stagg et al. 2021; Blair et al. 2018; Fairchild et al. 2013). Chapter 4 highlighted that facial expression recognition difficulties are found across an at-risk developmental sample in the absence of diagnosed conditions. This shared characteristic of facial expression recognition difficulties across various diagnosed conditions, as well as in children with emotional, cognitive, and/or behavioural problems without a diagnosis, underscores the potential for common underlying mechanisms driving difficulties in emotion recognition. Here, by adopting a transdiagnostic dimensional approach, I identified shared structural markers underlying facial expression recognition difficulties in an at-risk group of children .

Facial expression recognition is thought to rely on a network of brain regions, including visual, limbic, temporoparietal, and prefrontal regions. Structural MRI studies using VBM and SoBM have attempted to address the structural variations in typically developing populations and populations with neurodevelopmental conditions, such as autism, ADHD, and CD, highlighting markers of atypical development in areas linked to cognition, emotion, and behavior. Typically developing individuals showed correlation between facial expression recognition abilities with increased GMV in amygdala and fusiform gyrus (K. Zhao et al. 2013; de Castro L. Neves et al. 2015; Maat et al. 2016; Jung et al. 2021). Recent meta-analyses showed that individuals with autism have increased GMV in certain temporal and frontal regions and decreases in others, such as the anterior cingulate cortex and cerebellum compared to their neurotypical peers (Yang et al. 2016; Liloia et al. 2024; Mei et al. 2024). Similar investigations in ADHD reveal diminished GMV in frontal regions, while findings in CD indicate reduced GMV in regions associated with emotion processing and regulation (Y. Zhao et al. 2020; Long et al. 2022; Y. Gao et al. 2024; Tully et al. 2023).

Morever, these structural differences among populations with neurodevelopmental conditions were shown using SoBM. Applying it into autism, Grecucci et al. (2016) and Pappaianni et al. (2018) identified a specific gray matter network involving the frontal and temporal regions, including the inferior, middle, and superior frontal and temporal gyri, as well as the fusiform gyrus. Another study focusing on structural variations in ADHD utilised SoBM with over 250 individuals with ADHD and a matched control group. They identified an IC linked to ADHD that encompassed the occipital, frontal, pre- and post-central gyri, and the precuneus, demonstrating the structural variations in ADHD (Bralten et al. 2017).

Despite numerous functional imaging studies focusing on the disparities in task performance involving facial expressions between at-risk and typically developing populations, only few researchers have examined the structural markers underlying these differences. For example, Uono et al. (2022) investigated structural differences related to emotion recognition between individuals with and without autism. They found that gray matter volume in the right

inferior frontal gyrus was positively associated with recognition performance in typically developing individuals unlike in the autism group, suggesting potential differential structural mechanisms.

Taking a transdiagnostic approach, aligned with the RDoC framework, allows for the identification of common structural markers of facial expression recognition abilities among children (Fusar-Poli et al. 2019; Insel et al. 2010). The current study included two sources of recruitment: an at-risk sample of children who had previously been referred to the NDAU with emotional, cognitive, and/or behavioural difficulties, and a community sample of children without reported difficulties. Contrary to the previous chapter's inclusion of categorical comparison, this chapter sought to leverage the diverse spectrum of facial expression recognition abilities present within our combined sample. This focus on facial expression recognition abilities aimed to align the thesis with the RDoC This focus on facial expression recognition abilities aimed to align the thesis with the RDoC framework, utilizing this common domain to examine a diverse sample of children exhibiting varying levels of difficulties. Despite extensive prior research investigating the relationship between facial expression recognition difficulties and neural correlates within specific neurodevelopmental disorders, the current transdiagnostic approach addresses a notable gap by elucidating the structural markers of facial expression processing across a broader spectrum of abilities, grounded in the RDoC approach.

To achieve this goal, I employed both VBM and SoBM. While VBM detects voxel-wise volume differences, predominantly in gray matter, SoBM adopts a multivariate, data-driven approach to capture large-scale patterns of gray matter volume covariation across brain networks. SoBM offers advantages over traditional univariate analyses, notably in its data-driven approach which doesn't impose predefined models or hypotheses. It achieves this by focusing on naturally occurring patterns, underscoring that structural covariance may not align with prior expectations or theories. Finally, the identified networks in SoBM may be closely associated with functional networks, offering insight into the organisation of the

brain (L. Xu et al. 2009; Luo et al. 2023; Yoon et al. 2017). Adopting a SoBM approach can therefore provide complementary information on brain structure to univariate, traditional approaches such as VBM and, enhance our understanding of the link between brain structure and facial expression recognition ability. Leveraging both VBM and SoBM techniques, this study aimed to identify structural markers of facial expression recognition abilities across an at-risk sample.

5.2 Methods

5.2.1 Participants

The present study included 41 children aged 7 to 12 years. Within this sample, 25 (7 females) children had previously been referred to, and assessed within, the NDAU at the CUCHDS. Although these children were referred due to their emotional, behavioural and/or cognitive difficulties , they did not have an existing diagnosis at the time of referral, however at the time of taking part in the current study, one child had a diagnosis of autism, and another child had a clinical history of neurodevelopmental trauma. The remaining 16 (6 females) children were recruited from the community. This study was approved by the Cardiff University School of Psychology Ethics Committee. Written and verbal consent were obtained from the parents and children, respectively.

5.2.2 Questionnaires

Parental questionnaires on children's demographics and children's behavioural and emotional difficulties were completed on paper, at CUBRIC, Cardiff University. The demographics included questions like the age and gender of the child and the relation of the participant who filled out the questionnaires (e.g., mother, father, or carer), as well as the SDQ (described in Chapter 3).

Emotion Recognition Task

FER ability was assessed using the isolated FER task described in Chapter 3. As the sample for the current study was older relative to the cohorts examined in Chapter 3 and Chapter 4, and the ability to recognise negative facial expressions has a more protracted development compared to positive facial expressions (Lawrence et al. 2015; Widen 2013), the analyses in this chapter focused on negative facial expression recognition only (sad, fearful, and angry facial expressions). Furthermore, difficulties with negative facial expression recognition, rather than positive facial expressions, are more common across various neurodevelopmental conditions (Blair et al. 2018; Fairchild et al. 2013; Rappaport et al. 2021; Collin et al. 2013) which makes them more relevant to study in an at-risk sample.

5.2.3 Data Acquisition

Magnetic resonance imaging was acquired using a 3T CONNECTOM MRI scanner (32-channel radio frequency coil, Nova Medical), at the CUBRIC, Cardiff University, UK. T1-weighted anatomical images were obtained using a Magnetization Prepared Rapid Gradient Echo (MP-RAGE) sequence with the following parameters: TE = 2 ms, TR = 2300 ms, acquisition time = 5 min 35 sec, 192 slices, and voxel size of 1x1x1 mm. Children watched a movie during the scan. After completion of the structural MRI scan, diffusion and functional MRI scans were acquired in some children (25 minutes), however these scans are not analysed in the current chapter.

5.2.4 Design and Procedure

Children and parents who had visited the NDAU and consented to be contacted to participate in future research studies (NDAU-recruited sample), were invited to take part in the study. Additionally, children from the local community within South Wales (Community Sample (CS)), were recruited via social media, and university platforms e.g., Yammer, and CUBRIC weekly email newsletter. Children were aged 7 to 12 for both recruitment sources.

All parents and children were informed about the study procedure including a mock scanner practice session, an imaging session, and behavioural tasks. An information sheet, MR screening form, and COVID-19 screening forms were sent prior to their visit to CUBRIC. The entire visit took around 90-120 minutes, and participants were given a certificate of completion and a £20 gift voucher. First, a 30-min training session at the Mock MRI Scanner was completed, and parents filled out the consent and MRI safety screening forms. During this session, a researcher went through each step of the MRI procedure, including the use of headphones, the need to stay still during the scan, and the noise. The benefits of mock scanner training include reducing distress and anxiety, understanding the scanner environment, and less excessive movement resulting in better quality data (Buimer et al. 2020; de Bie et al. 2010). Behavioural testing took place in a cognitive testing lab at CUBRIC and took approximately 30 minutes. A researcher was with them throughout the tasks. Parents completed questionnaires regarding the child's temperament and characteristics. At the end of the study, the child and parent were debriefed. The visit procedure is depicted in Figure 5.1.

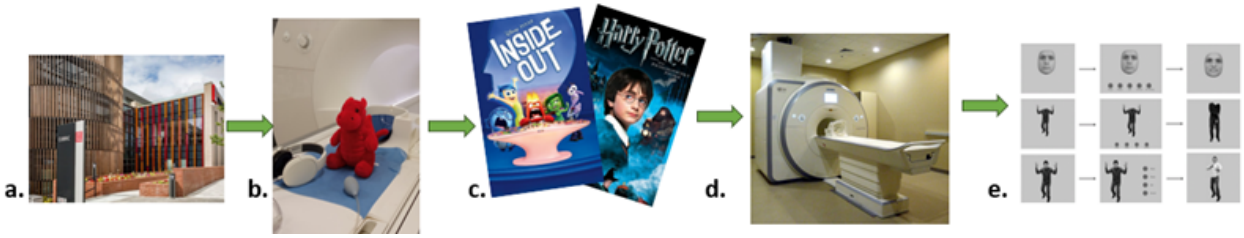

Figure 5.1: MRI visit procedure.
a. Meeting at the CUBRIC reception, b. Mock scanner practice, c. Movie choice, d. MRI scan, e. Behavioural tasks.

5.2.5 Data Analysis

Structural MRI Preprocessing and Quality Control

The preprocessing and analysis of the structural MRI data were run using SPM12 (https://www.fil.ion.ucl.ac.uk/spm/software/spm12/), CAT12 (https://neuro-jena.github.io/cat/),

and MATLAB 2021a (The MathWorks, MA, USA). First, T1-weighted images were visually inspected, and reoriented to the anterior commissure - posterior commissure using the Display tool in the SPM12. Before running the VBM analysis in CAT12 , customised paediatric Tissue Probability Maps (TPM) based on the age and sex of the current sample and a Diffeomorphic Anatomical Registration Through Exponential Lie Algebra (DARTEL) template were created by using the Cerebromatic Toolbox (COM) in order to improve the accuracy of tissue segmentation (Wilke et al. 2017). Next, the structural MRI images were segmented into GM, WM, and Cerebrospinal Fluid (CSF). The extracted GM maps were then spatially normalised to the study-specific paediatric template using DARTEL. Subsequently, the GM images were modulated with Jacobian determinants obtained from the normalisation process to maintain regional volumes. Default parameters in the CAT12 toolbox were applied unless indicated otherwise. Quality checks of the pre-processed data were based on the report generated by CAT12 and visual checks. These checks included Image Quality Ratings (IQR) for each participant, visual inspection of the tissue segmentation with the Single Slice Display, and the Check Sample Homogeneity tools in CAT12. IQR is an index in which image resolution, noise, and bias are detected automatically by CAT12 for each participant. The images of participants that have lower than the D range (percentage of 64) of IQR were excluded from the analysis (https://neuro-jena.github.io/cat/index.html), which resulted in the exclusion of three children who had been referred to NDAU. The final sample included 38 children, where 22 were NDAU-referred and 16 were community sample children. The processing pipeline for the structural imaging data is shown in Figure 5.2. Following the exclusion of NDAU-referred children who had lower than satisfactory IQR, a Mann-Whitney U-test for IQR was performed between NDAU-referred children and CS children and showed that they did not differ in the mean IQR (W=136.5, $p = 0.249$). Total Intracranial Volume (TIV) for each child was estimated from CAT12, to correct for individual differences in brain size of children in subsequent statistical analyses.

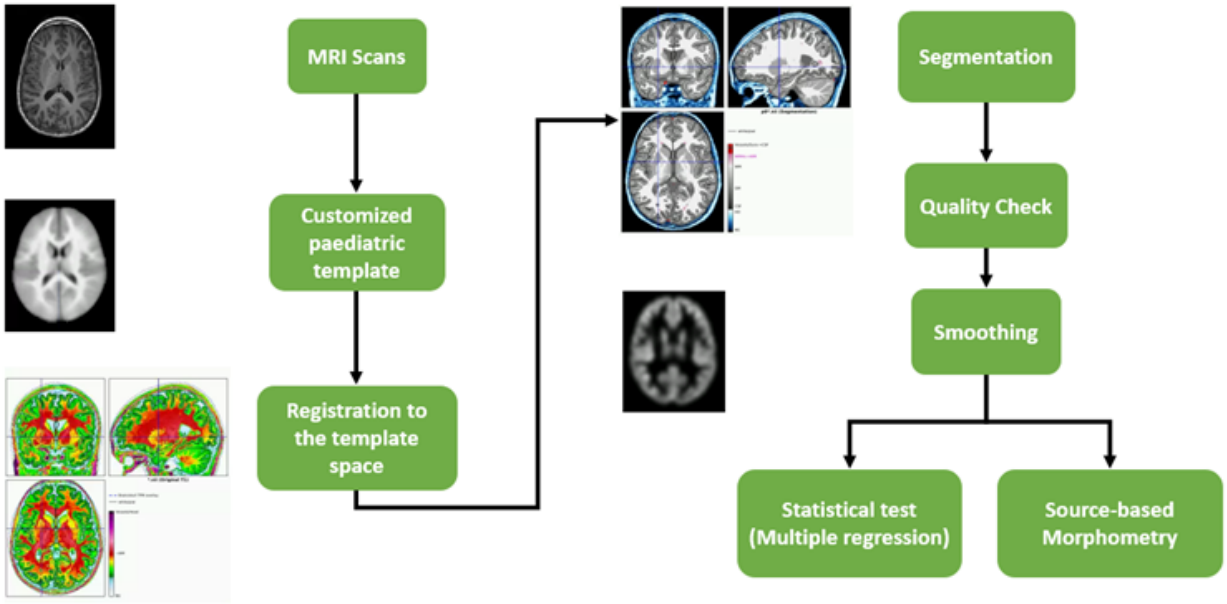

Figure 5.2: The processing steps of VBM using the CAT12 toolbox of SPM12 software.

Voxel-based Morphometry (VBM)

After the data acquisition and preprocessing, VBM analysis was performed via the CAT12 toolbox within SPM12. GM images were smoothed with an 8 mm Full Width Half Maximum (FWHM) kernel. The relationship between GM volume and children's negative FER ability was assessed by entering the smoothed GM images into a regression model with overall negative FER scores, where global scaling of TIV was also applied.

ROIs were established based on prior research into activation regions associated with FER processing. These encompassed the amygdala (Habel et al. 2007; Loughead et al. 2008), insula (Pohl et al. 2013; Sambataro et al. 2006), hippocampus (Miola et al. 2023), fusiform gyrus (C. H. Chen et al. 2006; Loughead et al. 2008), OFC (Groves et al. 2018; Rolls 2004), superior temporal gyrus (Wiggins et al. 2015; Domínguez-Borrs et al. 2009), middle temporal gyrus (Wiggins et al. 2015), anterior and middle cingulate cortex (Miola et al. 2023; Jongen et al. 2014), and thalamus (Loughead et al. 2008), bilaterally . The ten ROIs were defined based on the Automated Anatomical Labeling (AAL) atlas, using the WFU Pickatlas toolbox (Maldjian et al. 2003; Maldjian et al. 2004) in SPM12 (Figure 5.3). A Small Volume

Correction (SVC) for multiple comparisons (Family Wise Error (FWE) corrected at $p < 0.05$) was performed to explore the relationship between mean GMV in these Region of Interest (ROI)s and overall negative FER among children. The SVC was applied separately for each ROI, to control for multiple comparison bilateral masks were used.

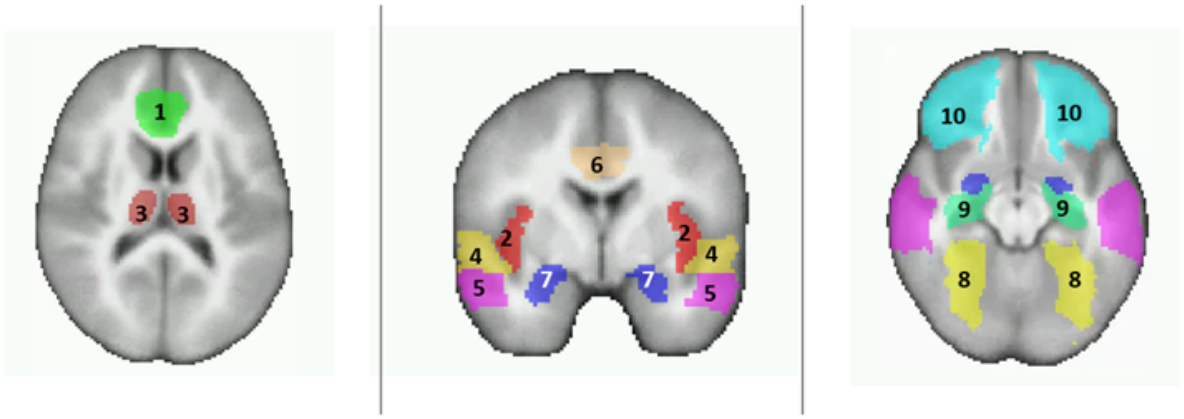

Figure 5.3: The ROI masks overlaid on the customised paediatric template.
1 - Anterior Cingulate, 2 - Insula, 3 - Thalamus, 4 - Superior Temporal Gyrus, 5 - Middle Temporal Gyrus, 6 - Middle Cingulate Gyrus, 7 - Amygdala, 8 - Fusiform Gyrus, 9 - Hippocampus, 10 - Orbitofrontal Cortex.

Source-based Morphometry (SoBM)

The preprocessing steps for SoBM were identical to those adopted for the VBM analysis (Grecucci et al. 2016; K. C. Wang et al. 2022). SoBM was carried out using the GIFT toolbox to perform ICA (https://github.com/trendscenter/gift), following the approach of previous studies (Grecucci et al. 2016; L. Xu et al. 2009). The smoothed GM images were used, and the Minimum Description Length (MDL) principle estimated the number of independent components as three. ICA was performed using a neural network algorithm (Infomax) that minimises the mutual information of the network outputs to identify natural grouping and maximally independent sources. ICA was repeated 20 times with Independent Component Analysis for Clustering and Visualisation (ICASSO), a technique that assesses the stability and consistency of the resulting independent components (ICs) across iterations. Reliability is measured by a quality index known as Quality Index (Iq), which falls on a scale from 0 to 1. This index essentially indicates how much the similarity within a cluster differs from

the similarity between different clusters (Himberg et al. 2004). All three components derived from the analysis of the gray matter images demonstrated a robust association with an Iq value exceeding 0.96, signifying remarkably stable ICA decomposition.

The analysis identified three IC maps, and these maps were thresholded at a Z-score of > 3.5. The Talairach coordinates of brain regions within the ICs were converted to Montreal Neurological Institute (MNI) space using (https://bioimagesuiteweb.github.io/webapp/mni2tal.html). This analysis resulted in a mixing matrix of 38 rows (one for each child) and three columns (IC). The columns contained loading coefficients, representing how much a child contributed to each IC. Correlation analyses were performed using the loading coefficients of each component and overall negative FER, controlling for TIV.

To explore the functional characterisation of the network of structural gray matter volume covariance associated with the recognition of negative facial expressions, I employed the Neurosynth decoder function (Yarkoni et al. 2011). Neurosynth contains a database of over 14,000 functional neuroimaging studies, each labelled with specific cognitive terms. Meta-analytic coactivation maps are generated based on the likelihood of each voxel across these functional studies being associated with a specific cognitive term. The decoder function of Neurosynth runs spatial correlation with meta-analytic coactivation maps corresponding to specific terms. This enables the identification of robust functional terms correlated with the structural gray matter volume covariation map identified in the SoBM analysis, as well as regions identified in the VBM analysis.

The behavioural data analysis was run on RStudio Version 2023.06 (RStudio, PBC, Boston, MA URL http://www.rstudio.com/). The figures were created using RStudio, JASP 0.18.0 (JASP Team, https://jasp-stats.org/), and FSLeyes Version 1.4.6 (FSL 6.0.5).

5.3 Results

5.3.1 Sample Characteristics

Demographic information and behavioural profiles for the sample as a whole, as well as NDAU-referred (N=22) and CS (N=16) children separately, are listed in Table 5.1. Two NDAU-referred children and three CS children are excluded from the SDQ summary due to incomplete data. The repeated analysis after excluding two children with clinical history/diagnosis did not show a change in the significant differences between groups in either Total SDQ ($p = 0.0011$) or overall negative FER ($p = 0.01$). The distribution of children's negative FER abilities is shown in Figure 5.4.

Variables	NDAU (N=22) Mean (SD)	CS (N=16) Mean (SD)	Overall (N=38) Mean (SD)	p-value
Age (years)	9.31 (1.25)	10.3 (1.50)	9.74 (1.44)	0.051
Gender (% Female)	7 (31.8%)	6 (37.5%)	13 (34.2%)	0.715
Total SDQ	21.4 (4.85)	14.5 (5.06)	18.6 (5.94)	**<0.001**
Internalizing Problems	11.1 (3)	7.27 (3.26)	9.53 (3.63)	**<0.001**
Externalizing Problems	10.4 (2.66)	7.31 (2.29)	9.24 (2.92)	**0.003**
Overall Negative FER	0.854 (0.081)	0.935 (0.068)	0.888 (0.085)	**0.004**

Table 5.1: Sample Characteristics.
The demographic and behavioural data summary for children from each recruitment source is shown with mean and standard deviation values. Differences between NDAU and CS-referred children for each variable were analysed using the Mann-Whitney test for continuous variables and chi-square for a categorical variable (gender). SDQ = Strengths & Difficulties Questionnaire; FER = Facial Expression Recognition.

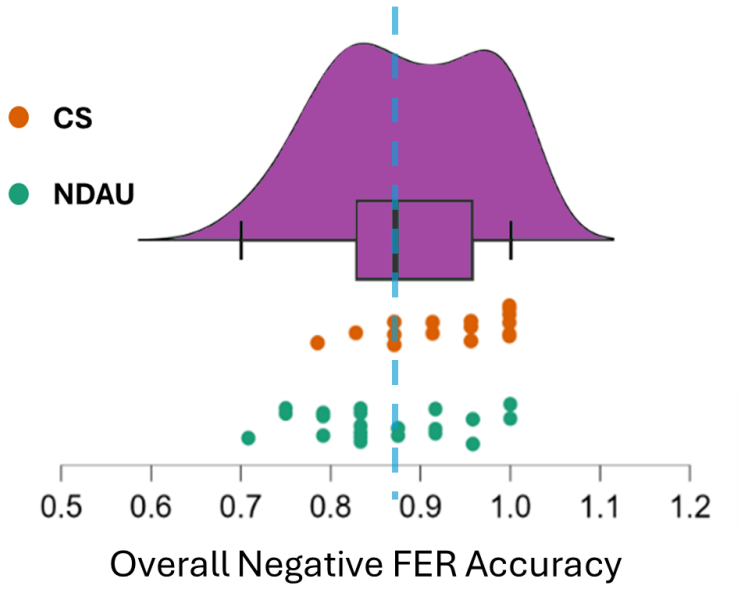

Figure 5.4: The distribution of negative FER abilities.
Children recruited from NDAU (green dots) and CS (orange dots). The yellow line represents the mean negative FER for whole sample.

5.3.2 VBM Results

A full list of clusters showing positive and negative correlation of GMV within ROIs and negative FER at p<0.001 uncorrected at the whole-brain level are shown in Appendix A1 and B1. Within the ROIs, a significant positive correlation emerged between GMV within the left middle temporal gyrus and the recognition of negative facial expressions (SVC $p < 0.05$), while controlling for TIV (Figure 5.5, Table 5.2), such that better negative facial expression recognition was related to greater grey matter volume in left middle temporal gyrus. After using bilateral Middle Temporal Gyrus (MTG) mask to control for multiple comparisons, the p-value remained smaller than 0.05 ($p = 0.048$). No other ROI showed a significant relationship with negative FER ability following small-volume-correction for multiple comparisons.

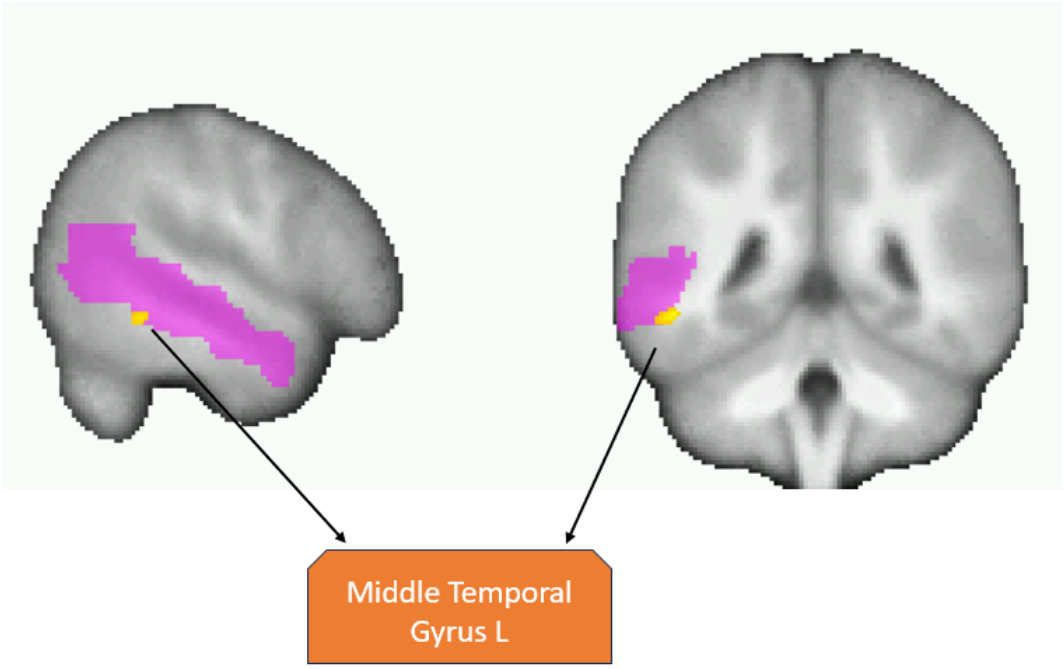

Figure 5.5: VBM results.
The yellow overlap depicts the region within middle temporal gyrus that showed higher grey matter volume with better negative facial expression recognition ($p < 0.05$, SVC). The left middle temporal gyrus ROI mask used for SVC is shown in pink.

ROI Name	Direction	Cluster size (voxels)	Peak-level FWE	T	MNI Coordinates
Middle Temporal Gyrus L	Positive	30	***0.025**	4.39	-52 -45 10

Table 5.2: ROI, peak coordinates, and small-volume corrected statistics (p<0.05).

5.3.3 Source-Based Morphometry

The three ICs identified by SoBM are displayed in Figure 5.6. Each of these ICs represents spatially independent, distinct patterns of GMV changes across brain regions. The first IC identified a structural network predominantly in the cerebellum (Figure 5.6a). The second IC identified a network comprised of MTG, Premotor Cortex, Postcentral Gyrus, Precuneus, and Inferior Parietal Lobule (IPL) (Figure 5.6b). The third IC identified a small cluster in Middle Frontal Gyrus (MFG) only (Figure 5.6c).

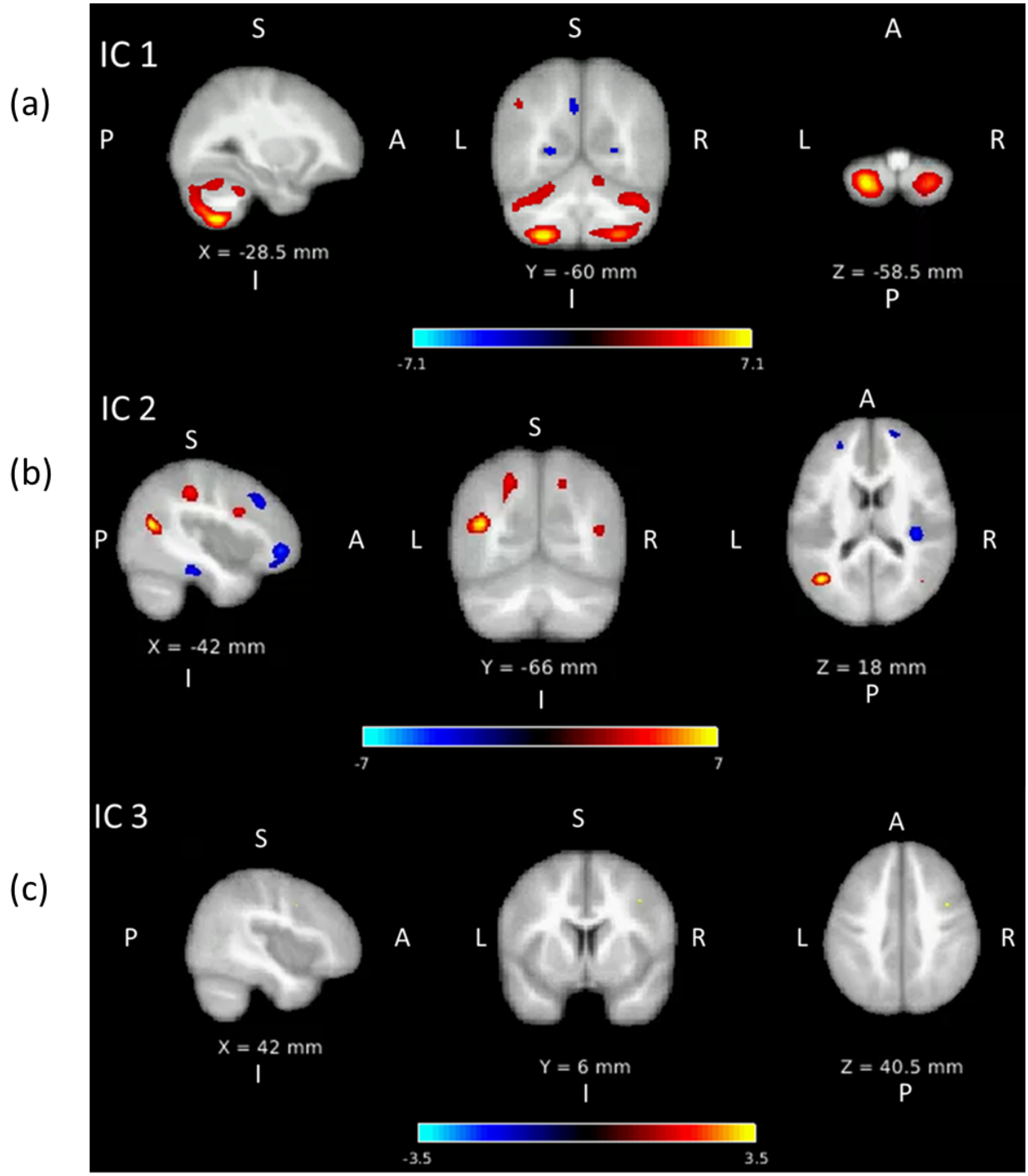

Figure 5.6: SoBM Independent Components of grey matter volume covariance. Three independent components were identified by SoBM and are depicted below following thresholding at $Z > 3.5$. Regions with increased GMV are shown in hot colours, whereas cool coloured regions represent decreased GMV.

Brain Behaviour Correlations

To reveal any links between negative FER ability and the ICs, a Spearman's rank correlation was run between the loading coefficients for each IC and negative FER ability. There was a significant negative correlation between the loading coefficients of IC 2 and overall negative FER performance (ρ = -0.43, p = 0.0072; Figure 5.7a; controlling for TIV (p = 0.014)). This finding suggests that children with lower overall negative FER abilities contribute more to the structural network of gray matter covariance identified in IC 2. Specifically, children with lower negative FER abilities have more GMV in the increased GMV (positive) areas and less GMV for the decreased GMV (negative) areas. A detailed list of each brain region in this structural network is presented in Table 5.3. It is noteworthy to highlight that children recruited via the NDAU vs CS did not differ in their loading coefficients for IC 2 (W=137, p=0.258), this lack of difference persisted even after excluding children with diagnosis from the analysis (W=123, p=0.274). The link between overall negative facial expression recognition performance and loading coefficients within each sub-sample [NDAU (ρ = -0.32, p = 0.14) and CS (ρ = -0.47, p = 0.067)] did not reach significance. Neither the IC 1 loading coefficients (ρ = -0.055, p = 0.74) nor the IC 3 loading coefficients (ρ=-0.21, p = 0.22) revealed any significant association with overall negative FER.

Positive	**Vol cc³ L/R**	**Z-score L/R**	**MNI X, Y, Z L/R**
Middle Temporal Gyrus	1.7/0.1	7.0/3.7	-43 -65 18/42 -65 14
Premotor Cortex	0.3/0.6	4.5/5.3	-39 -34 46/14 -52 67
	1.1/0.6	5.2/4.2	-50 -26 43/14 -50 70
Parahippocampal Gyrus	0.3/0.1	4.7/3.5	-33 -30 -21/35 -25 -24
Inferior Frontal Gyrus	0.2/0.0	4.4/None	-43 11 27/None
Precuneus	0.7/0.3	4.3/4.4	-13 -72 51/17 -71 54
Cerebellar Tonsil	0.1/0.3	3.7/4.3	-2 -55 -45/1 -55 -49
Inferior Parietal Lobule	0.6/0.0	4.2/None	-42 -34 49/None
Superior Parietal Lobule	0.2/0.3	3.9/4.2	-22 -66 51/21 -47 67
Precentral Gyrus	0.3/0.6	3.8/4.1	-58 -12 32/61 -10 28
Middle Frontal Gyrus	0.1/0.1	4.1/3.7	-38 14 27/43 -4 49
Superior Temporal Gyrus	0.1/0.0	3.9/None	-49 -59 11/None
Inferior Semi-Lunar Lobule	0.1/0.1	3.5/3.6	-2 -58 -48/1 -59 -45
Negative			
Middle Frontal Gyrus	1.9/1.6	5.2/5.9	-46 46 -10/23 32 -23
Inferior Frontal Gyrus	1.1/0.8	5.4/5	-27 21 -27/23 27 -24
Superior Temporal Gyrus	0.3/0.1	4.8/3.8	-27 19 -29/26 18 -30
Superior Frontal Gyrus	0.6/1.2	4.7/4.6	-28 58 -7/23 64 -9
Orbitofrontal Cortex	0.0/0.2	None/4.5	None/20 35 -22
Insula	0.0/0.4	None/3.8	None/40 -26 18
Fusiform Gyrus	0.1/0.1	4.1/4	-45 -32 -23/46 -25 -26
Medial Frontal Gyrus	0.1/0.1	3.5/3.8	-15 68 6/14 66 -17
Precentral Gyrus	0.1/0.0	3.7/None	-43 24 38/None
Cerebellum	0.1/0.0	3.6/None	-11 -82 -34/None

Table 5.3: Brain regions involved in IC 2 with volume, Z-score, and MNI coordinates in the Left (L), and Right (R) hemispheres.
Positive refers to regions that show increased GMV within IC 2, whereas negative refers to regions that show decreased GMV. None = Not significant ($|Z| > 3.5$) contribution of the component.

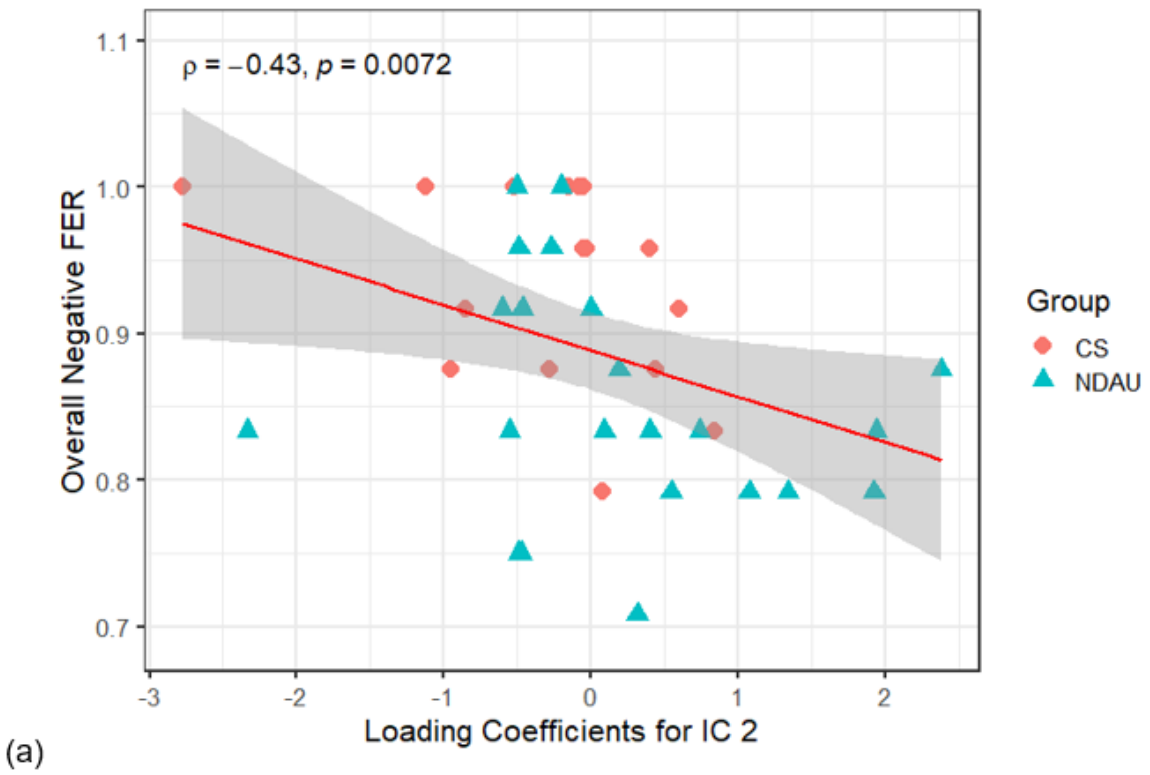

Figure 5.7: Representation of brain and behaviour in negative FER.
(a) The Relationship between IC 2 loading coefficients and Overall Negative FER. There was a significant negative relationship between the loading coefficients for IC 2 and negative FER ability ($\rho = -0.43$, $p = 0.0072$). The blue triangles represent NDAU-referred children, the pink circles represent CS children. The shaded area represents the 95% confidence interval, and the red line indicates the regression line. (b) The covariance of overall negative FER performance and loading coefficients of IC 2 on spider plot.

Functional Decoding via NeuroSynth

Using Neurosynth, the functional terms associated with regions of increased and decreased GMV within the network of gray matter volume covariation linked to negative facial expression recognition were identified. The top 15 unique functional terms are visually represented in a word cloud (Figure 5.8). Anatomical terms such as "parietal" or "prefrontal" were excluded from the list; near duplicates such as "movements" and "movement" were presented with one term. The top 10 terms associated with the VBM-identified region are also visually represented in a word cloud following the aforementioned principles (Figure 5.9).

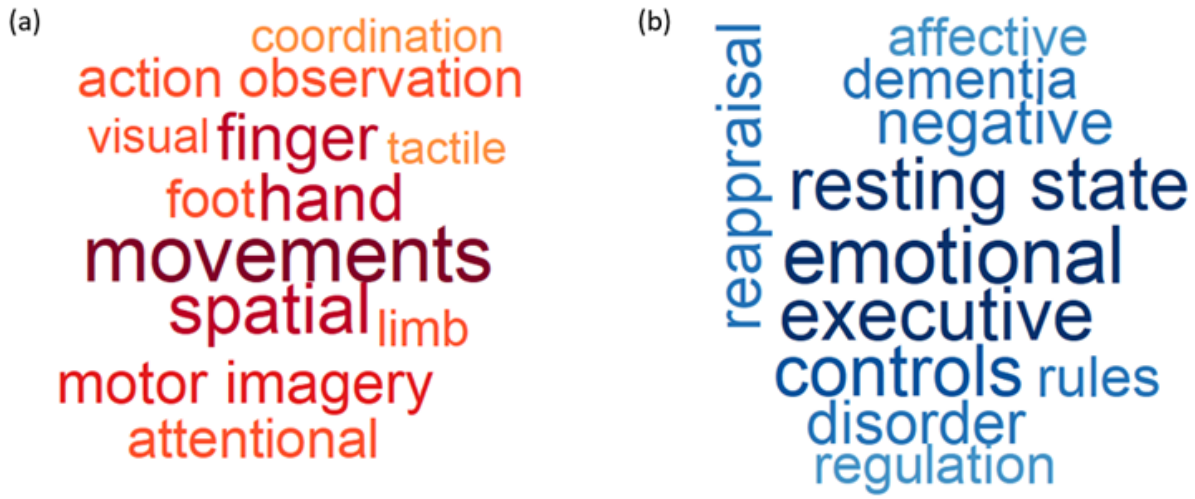

Figure 5.8: Functional decoding terms of the network of structural covariance. (a) Functional terms showing correlation with regions of increased gray matter volume within the network of structural covariance. (b) Functional terms showing correlation with regions of decreased gray matter volume within the network of structural covariance. The size of the font represents the strength of the correlation between the identified structural network map and term-based meta-analysis maps generated by Neurosynth.

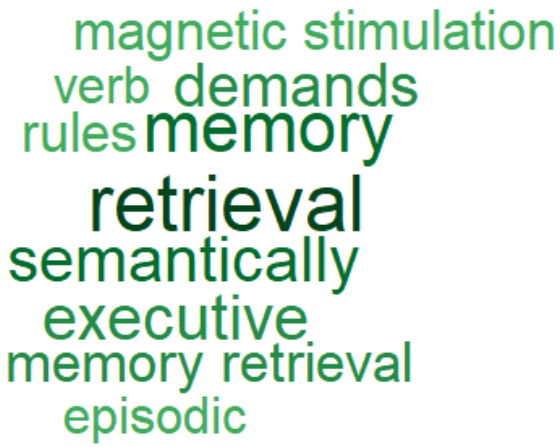

Figure 5.9: Functional decoding terms correlating with the VBM results.
The size of the font represents the strength of the correlation between the VBM results and term-based meta-analysis maps generated by Neurosynth.

5.4 Discussion

In this study, I employed both VBM and data-driven SoBM approaches to discern structural variation associated with the recognition of negative facial expressions within an at-risk sample, consisting of both children from the community and children who had previously been referred by their schools due to emotional, cognitive, and/or behavioural difficulties. A VBM analysis identified a region in left MTG with significantly greater GMV in children with better negative FER. Furthermore, a SoBM analysis identified a network of GMV covariance associated with children's negative FER ability, which included regions of MTG, premotor cortex, MFG, and IFG. Functional terms associated with this structural network included emotion processing, motor control, and executive function.

The observed increase in GMV within the left MTG among children with higher performance in negative FER, as evidenced in the VBM analysis, is interesting when considering previous research. The left MTG has previously been reported to be important in language processing and semantic memory (J. Li & Pylkkänen 2021; Matsui et al. 2013; Morese et al. 2022), alongside its involvement in face processing (Adamson & Troiani 2018; Critchley et al. 2000), and the perception of emotional facial expressions (Jongen et al. 2014; Ihme et al. 2014).

Language plays a crucial role in recognising facial expressions by connecting emotional words to behaviour. Research has demonstrated that a greater understanding of emotional vocabulary improves the accuracy of identifying facial emotions (Adolphs 2002; Barrett et al. 2007). The MTG integrates linguistic information with visual and emotional cues, potentially contributing to the connection between language and facial emotion recognition. Furthermore, functional activation differences in the MTG have been linked to impaired language comprehension and facial emotion recognition in neuroimaging meta-analyses (Fusar-Poli 2019; Vytal & Hamann 2010), suggesting an overlap of both functions within this brain region. This insight has led researchers to explore the structural and functional differences within MTG among individuals with neurodevelopmental conditions. Structural and functional MRI studies have revealed that neurodevelopmental populations experiencing social and communication difficulties, such as those with autism or ADHD, exhibit abnormalities in both the structure and function of the MTG (M. X. Xu & Ju 2023; Yun et al. 2017; Y. Zhao et al. 2020). Overall, current research indicates that MTG may act as a potential hub for integrating linguistic and emotional information to facilitate the recognition of diverse facial expressions within a semantic framework.

SoBM, utilising a multivariate approach, identifies brain networks showing covariation in GMV (L. Xu et al. 2009). Previous studies suggest that SoBM is particularly advantageous for detecting structural biomarkers across individuals as it does not require a specific, a priori hypothesis. Moreover, SoBM provides additional insights into anatomical grouping of regions. This contrasts with VBM, which identifies a set of regions however does not recognise the relationships among those regions. For instance, the complexity of anatomical changes among individuals with autism spans a spectrum. SoBM enables researchers to study the structural network differences of individuals with autism compared to their neurotypical peers, enabling the recognition of relationships among naturally grouped regions. Therefore, SoBM provides a more effective framework to identify biological markers within a network compared to univariate approaches, especially for heterogeneous populations (Grecucci et al.

2016; Pappaianni et al. 2018; L. Xu et al. 2009). In the current study, I found a network of structural covariance, which included MTG, premotor cortex, MFG, and IFG, which was linked to negative facial expression recognition across a diverse sample of children. While this network of structural GMV covariance linked to facial expression recognition does not directly overlap with a known functional network, these regions have been variously been linked to facial perception, language, ToM, and emotional experience, (J. Zhang et al. 2022; M. X. Xu & Ju 2023; van der Velde et al. 2015; Frühholz et al. 2009), suggesting that the network identified is likely to support facial expression recognition across domains of function.

The structural network of gray matter volume covariation, which is associated with facial expression recognition abilities, encompasses various regions as previously mentioned. Notably, the functions of the middle temporal gyrus include language processing, semantic memory (J. Li & Pylkkänen 2021; Matsui et al. 2013; Morese et al. 2022), facial perception, cognitive processing of emotions, and emotional experience (K. C. Wang et al. 2022; J. Zhang et al. 2022; Kitada et al. 2010; Quintana et al. 2003; Pannekoek et al. 2013). Additionally, MTG is a part of the default mode network with its role in language and mentalising (Whitney et al. 2011; J. Xu et al. 2015; Papeo et al. 2019). Previous functional MRI studies demonstrated that premotor cortex is activated in response to negative facial expression images, imitation of facial expressions, and pain stimulus (van der Velde et al. 2015; Regenbogen et al. 2012; Lenzi et al. 2013; Ogino et al. 2007). This suggests that the collective contribution of these regions in the network of structural covariance might reflect the complex phenomenon of facial emotion recognition, and the multiple domains supporting this ability. In sum, the regions with increased GMV within the network, namely MTG and premotor cortex, exhibit characteristics associated with cognitive aspects of emotion processing, highlighting the relevance of these regions to facial emotion recognition. On the other hand, those regions showing decreased GMV are thought to be more directly involved in emotion processing. For instance, the MFG has been implicated in prior fMRI studies for its role in perceiving fearful, angry, painful facial expressions, as well as in memory tasks involving fearful faces (Frühholz

et al. 2009; Ballotta et al. 2018; Carpenter et al. 2015). Perception of familiar faces, and ToM has been found connected with the increased activation of the IFG among previous studies (Eger et al. 2005; Kumfor et al. 2015; Hulvershorn et al. 2012). Overall, the network of structural covariance encompasses brain regions involved in emotion processing.

Similarly, functional decoding from Neurosynth revealed a correlation between increased GMV regions of the SoBM results, and motor functions, whereas VBM results showed correlation with language and memory-related terms. However, the regions displaying decreased GMV in the SoBM results were correlated with functional terms associated with emotion, executive function, and resting state. Notably, the increased GMV regions identified in both the SoBM and VBM results appear to be related to cognitive aspects of facial emotion processing (Alaerts et al. 2015; Sato et al. 2023; Enticott et al. 2008). The regions exhibiting decreased GMV in the SoBM results were more directly aligned with facial emotion processing. This was evidenced by our finding that children with lower negative facial expression recognition abilities contributed more to these decreased GMV areas.

Rather surprisingly, the amygdala was not identified as a region of increased or decreased GMV linked to FER, despite the fact that numerous previous studies have shown a strong link between emotion processing and the amgydala (Fusar-Poli et al. 2009; Gur et al. 2002; K. Zhao et al. 2013; A. T. Wang et al. 20044). There are a few potential explanations regarding the lack of amygdala GMV change here. Firstly, the sample size was relatively small that could limit the statistical power and make it difficult to detect subtle differences in brain regions like the amygdala. Secondly, the heterogeneity of the sample may have played a crucial role. The at-risk group of children display a range of difficulties at emotional, cognitive, and behavioural levels, potentially leading to distinct neural patterns, as well as the common ones identified here. Additionally, the amygdala is particularly involved in processing fearful facial expressions. I assessed overall negative facial expression recognition including anger, sadness, and fear. This broader focus might have weakened any potential link to fearful expressions, which are more directly associated with the amygdala.

Prior studies using SoBM identified differences in structural covariance networks within neurodevelopmental samples, such as autism, ADHD (Grecucci et al. 2016; Pappaianni et al. 2018; Duan et al. 2021). While these studies primarily focused on differences between neurodevelopmental diagnostic groups and their neurotypical peers, the observed profile of structural network differences shows similarities to those of found in the current sample, including MTG, IFG and MFG. Despite the current study encompassing children with various levels of facial expression recognition abilities, but no diagnosed conditions, these findings indicate a potential continuum between children from the community, those referred due to their emotional, cognitive, and/or behavioural difficulties, and those diagnosed neurodevelopmental conditions, highlighting their interconnectedness in relation to structural brain variability.

The rationale for adopting a wider transdiagnostic dimensional approach in this chapter, by recruiting children from various sources, requires clarification, particularly given the group comparison analyses conducted in the previous chapter. In the previous chapter, the aim was to uncover the underlying mechanisms shaping facial expression recognition within at-risk and neurotypical children, focusing on the influence of body context. Despite at-risk children exhibiting lower proficiency in facial expression recognition, all children displayed a similar mechanism underlying the influence of context, suggesting similarities in underlying emotion processing. In other words, NDAU-referred children and neurotypical children who had similar facial expression recognition abilities, also showed similar influence of context. Expanding on these findings, the present chapter aligns with the RDoC framework to integrate children from diverse recruitment sources, to capture a broad spectrum of facial expression recognition abilities, regardless of their extended behavioural profile. The Systems for Social Processes domain of the RDoC, which includes facial expression recognition, serves as a foundation for this transdiagnostic approach, aiding in the identification of common structural markers of facial expression recognition across children, regardless of diagnostic categories. Departing from traditional group comparisons allows for a more nuanced exploration of potential markers

of facial expression recognition abilities. It is important to highlight that those children recruited from NDAU and those recruited from the community did not differ in terms of how much they contributed to the identified structural network. The current results support the notion that transitioning from group comparisons to a broader, RDoC-based dimensional approach can provide novel insights into structural brain networks associated with facial expression recognition abilities (Apperly et al. 2024; Fusar-Poli 2019).

5.4.1 Strengths and Limitations

This study should be considered in light of its strengths and limitations. Firstly, employing a transdiagnostic dimensional approach, I aimed to identify potential structural markers supporting facial expression recognition abilities. This approach entailed including children with varying levels of facial expression recognition abilities from diverse recruitment sources, regardless of whether they fit neatly into specific diagnostic categories. By treating the range of FER abilities as a common trait, I could explore structural markers implicated in FER across at-risk children (Fusar-Poli 2019; Fusar-Poli et al. 2019; Insel et al. 2010).

Another clear strength of this research lies in the utilisation of VBM and SoBM, which offer complementary information. While VBM indicates local changes in GMV, SoBM identifies patterns of GMV covariance. By integrating these methods, the study enhances the validity and reliability of its findings while also boosting sensitivity to detect GMV changes that might be overlooked by using only one method. Notably, SoBM effectively eliminates sources of noise, resulting in cleaner data (L. Xu et al. 2009; Vacca et al. 2023). Moreover, as a data-driven approach, it is particularly effective for identifying GMV changes across heterogeneous samples. By incorporating SoBM alongside VBM, we can more effectively capture the nuanced structural differences associated with these conditions, thereby providing a more comprehensive understanding of the underlying structural markers.

While the findings contribute valuable insights, certain limitations should be taken into account. Although the relationship between the MTG and negative facial expression recognition

performance remained significant in the VBM analysis after applying a bilateral mask, this relationship did not survive Bonferroni correction. Therefore, the VBM results should be interpreted with caution. The relatively small sample size may affect generalisability, highlighting the need for careful interpretation. Future studies should involve larger samples of diverse groups with varying levels of FER performance to pinpoint more specific structural changes in at-risk sample of children .

5.5 Conclusion

To sum up, this study investigated the underlying structural markers of facial expression processing among children with various levels of facial expression recognition ability. I identified a structural network of gray matter covariance across the group comprising MTG, premotor cortex, MFG, and IFG, regions known for their roles in facial perception, emotion processing, and social cognition. This network of structural covariance was related to individual differences in negative facial expression recognition ability. The current chapter provides insight into structural markers associated with facial expression recognition across a diverse sample of children with different behavioural profiles.

Chapter 6

Exploring Neural Responses to Naturalistic Stimuli in Children

6.1 Introduction

Chapter 4 involved examining facial expression recognition in context in typically developing children and children with emotional, cognitive, and/or behavioural difficulties. The results of that chapter revealed that children with emotional, cognitive, and/or behavioural difficulties showed overall diminished facial expression recognition abilities. Nonetheless, they maintained the same underlying integration mechanism as their typically developing peers, wherein facial expression recognition ability served as the predictor of the biasing influence of bodily emotion during their judgements of facial expressions. The findings from Chapter 5 showed that unique patterns of gray matter covariance were related to facial expression recognition ability across children with a range of abilities and behavioural profiles. In the current chapter, I wanted to expand on the structural imaging findings by studying functional activation in response to watching an emotional movie clip and its relationship to facial expression recognition abilities in the same group of children.

The emergence of recent neuroimaging methodologies has not only paved the way for investigating the intricacies of the social brain but has also facilitated the utilisation of naturalistic stimuli, such as movies, to delve into socioemotional processing. The ISC approach has emerged as a valuable tool in investigating the degree to which brain activity correlates or synchronises across individuals exposed to the same stimulus (P. A. Chen et al. 2020; E. S. Finn et al. 2020; Hasson et al. 2004). By leveraging this correlation or synchrony across individuals, researchers can uncover the common underlying functional mechanisms of specific behaviours or cognitions. For example, Hasson, Nir, Levy, Fuhrmann, & Malach (2004) showed a high level of synchrony in the activation of the visual cortex in response to visual stimuli across individuals. This synchronised brain activation, measured by ISC, illustrates commonalities in how the human brain responds to visual stimuli by mitigating noise and idiosyncratic responses. Departing from traditional experimental paradigms, ISC approach offers the opportunity to employ naturalistic stimuli such as movies and narratives, which more accurately reflect authentic social interactions, for the study of social cognition. Consequently, the utilisation of such naturalistic stimuli enables the identification of neural networks that synchronise across individuals in response to emotional cues, for example, thereby mirroring the complexities of real-world social experiences (Nastase et al. 2019; Saarimäki 2021). Indeed, ISC has found widespread application in previous research across populations with neurodevelopmental conditions, and mood disorders, e.g., ADHD, autism, and social anxiety (Camacho, Balser, et al. 2023; Salmi et al. 2020; Skaribas 2020). Individuals with these conditions have been shown to exhibit weaker ISC compared to their neurotypical peers, suggesting that their atypical profiles may lead to deviations from neurotypical brain activation synchrony. Altogether, ISC enables the detection of similarities and/or differences in brain activity synchrony across individuals, both within specific populations, as well as across populations. This renders ISC a valuable tool for inferring shared mechanisms across heterogeneous, diverse populations.

Previous research on neurodevelopmental conditions and ISC has primarily focused on

similarities and/or differences between individuals with these conditions and neurotypicals during the viewing of social interactions. Ou et al. (2022) found reduced synchrony in key brain regions, namely middle temporal gyrus, temporal pole, and cerebellum, among autistic individuals. They suggested that this could indicate greater variability in functional specialisation within these regions in the autism group. Similarly, another study found decreased ISC in temporal, frontal and visual cortex areas in young adults with autism compared to their neurotypical peers. They hinted that atypical brain synchronisation in the autistic group might be potentially due to weaker modulation of brain regions in response to naturalistic stimuli (Kotila et al. 2021).

This pattern of weaker synchrony in response to naturalistic stimuli is also observed in individuals with ADHD. Salmi et al. (2020) demonstrated weaker ISC in the visual cortex, temporoparietal junction, superior temporal cortex among individuals with ADHD during the viewing of social interactions compared with a neurotypical group. Furthermore, they investigated the relationship between ISC and ADHD symptoms, revealing distinct ISC patterns associated with impulsivity and inattention in frontal, temporal, and limbic regions. Collectively, these studies highlight that individuals with neurodevelopmental conditions exhibit weaker ISC in response to social stimuli, which in turn may correlate with their behavioural characteristics.

However, adopting a transdiagnostic approach, as mentioned in Chapter 4 and Chapter 5, offers a broader perspective by capturing a spectrum of behavioural characteristics that cross diagnostic boundaries and categories rather than focusing on behaviour within a single diagnosis (Fusar-Poli 2019; Insel et al. 2010). Focusing in the RDoC framework, which promotes a dimensional approach to understanding psychological processes, this study centers on shared patterns of brain synchrony across children with diverse behavioural profiles and a wide range of facial expression recognition abilities. In line with the Systems for Social Processes domain of the RDoC, the study specifically compares children based on their facial expression recognition ability rather than traditional group comparisons based

on broader emotional, cognitive, and/or behavioural profiles (e.g., NDAU-referred vs non-referred children). This approach enables the exploration of differences in brain activation synchrony as they relate to FER abilities within a diverse sample of children. By utilising a transdiagnostic, RDoC-aligned approach, I aim to achieve a clearer understanding of the neural mechanisms underlying emotion processing across children with varying levels of facial emotion recognition abilities.

6.1.1 The Current Study

In the current study, I employed ISC analysis on fMRI data obtained in a diverse sample of children while watching an emotional movie clip. I aimed to elucidate similarities and differences in brain activation synchrony in response to emotional, naturalistic stimuli between children with lower and higher FER abilities. This investigation will uncover shared patterns of brain synchrony linked to FER ability, shedding light on the complex nature of emotion processing within a sample of children with varying levels of facial emotion recognition abilities.

6.2 Methods

6.2.1 Participants

The present study included 26 children aged 7-12 years, which included 12 (4 females) children who had been previously referred to the NDAU due to their emotional, cognitive, and/or behavioural difficulties, and 14 (6 females) children recruited from the community. The current sample is a subgroup of the sample described in Chapter 5. The participants in this subsample share the same characteristics and selection criteria as those outlined previously. The study was approved by the Cardiff University School of Psychology Ethics Committee. Written and verbal consent were obtained from parents and children, respectively.

6.2.2 Materials

Questionnaires

Parental questionnaires on children's demographics and children's behavioural and emotional problems were completed on paper, at CUBRIC, Cardiff University. The demographics and the SDQ were completed by the parent (as described in Chapter 5).

Emotion Recognition Task

Isolated FER task was presented to children, as described in Chapter 3.

Following the findings from the previous chapter, the performance in negative facial expressions was used to group children with low and high performance in negative FER to detect functional differences in response to a naturalistic movie with emotional content.

Movie Stimuli

During the fMRI scanning, children watched a 10-minute segment of the animated movie "Despicable Me" (Universal Pictures, 2010). This movie clip has previously been used in the Healthy Brain Network (Alexander et al. 2017). The clip contains a mix of positive and negative emotional scenes and revolves around social relationships. It delves into complex themes such as internal conflicts and the bond between children and their adoptive parent, which can involve both connection and separation. According to coding of emotional components of the "Despicable Me" clip, emotion throughout the movie clip is primarily negatively-valenced (Camacho, Balser, et al. 2023; Camacho, Nielsen, et al. 2023).

6.2.3 Data Acquisition

Magnetic resonance imaging was acquired using a 3T CONNECTOM MRI scanner (32-channel radio frequency coil, Nova Medical), at the CUBRIC, Cardiff University, UK. T1-weighted anatomical images were obtained using a MP-RAGE sequence with the following parameters:

TE = 2 ms, TR = 2300 ms, acquisition time = 5 min 35 sec, 192 slices, and voxel size of 1x1x1 mm. Functional images were acquired using a whole-brain Echo-planar Imaging (EPI) sequence with parameters of TE = 35 ms, TR = 1500 ms, acquisition time = 10 min 54 sec, voxel size = 2x2x2 mm, flip angle = 70°, slice = 66, bandwidth = 1976 Hz/pixel, field of view = 220 mm, multiband acceleration factor = 3. In addition to the structural and functional MRI scanning, diffusion MRI scanning was performed with an acquisition time of 16 min 14 sec. The diffusion scan is not analysed here. After quality check of the imaging data, 3 children from NDAU recruitment and 1 child from CS recruitment were excluded due to low quality image and high movement (mean Framewise Displacement (FD) being higher than overall sample mean FD + 1 SD). This remained the sample with 9 children from NDAU, and 11 children from CS.

6.2.4 Design and Procedure

Design and procedure were as explained in Chapter 5.

6.2.5 Data Analysis

6.2.6 Behavioural Data

Children were median-split (Mdn = 0.875) into one of two groups, depending on their overall negative FER performance. The demographics and behavioural measures of these groups as low (N=9) and high (N=13) FER ability are shown in Table 6.1. These two groups did not differ in their levels of emotional and behavioural difficulties which were measured by SDQ (W = 40.5, p = .241, neither did they differ in age or gender (W= 66.5 p = .615, $\chi^2(1) = 0.646$, $p = .421$). Additionally, these groups categorised by FER abilities exhibited no significant differences in recruitment sources ($\chi^2(1) = 0.188$, $p = .665$), indicating that children displayed a spectrum of FER abilities irrespective of their levels of emotional, cognitive, and/or behavioural difficulties. The demographics and behavioural measures of each recruitment source were shown in Table 6.2.

	Low FER Ability Group Mean (SD)	**High FER Ability Group Mean (SD)**	**p-value**
Age (in years)	10.5 (1.95)	10.12 (1.27)	0.615
Gender (% Female)	2 (22.2%)	5 (38.5%)	0.421
Negative FER Accuracy	0.829 (0.061)	0.968 (0.039)	<0.001
Total SDQ	14.2 (4.68)	17.5 (7.13)	0.24
Internalizing Problems	6.29 (2.87)	9.15 (4.32)	0.115
Externalizing Problems	7.57 (2.82)	8.38 (3.18)	0.255
Recruitment Source (% NDAU)	5 (45.45%)	6 (54.54%)	0.665

Table 6.1: The demographics and profile of the low and high FER ability groups. The differences between the groups for each variable were analysed using the Mann-Whitney test for continuous variables and chi-square for a categorical variable (gender).

Variables	**NDAU (N=11) Mean (SD)**	**CS (N=11) Mean (SD)**	**Overall (N=22) Mean (SD)**	**p-value**
Age (years)	9.75 (1.637)	10.8 (1.33)	10.3 (1.56)	0.147
Gender (% Female)	4 (36.4%)	3 (27.3%)	7 (31.8%)	0.647
Total SDQ	16 (5.67)	16.3 (7.22)	16.2 (6.33)	0.817
Internalizing Problems	7.9 (3.6)	8.4 (4.62)	8.15 (4.04)	0.963
Externalizing Problems	8.2 (2.82)	8 (3.33)	8.1 (3.01)	1
Overall Negative FER	0.902 (0.1)	0.920 (0.06)	0.911 (0.08)	0.893

Table 6.2: The demographics and profile of children recruited from NDAU and community. The differences for each variable were analysed using the Mann-Whitney test for continuous variables and chi-square for a categorical variable (gender).

6.2.7 Preprocessing

The preprocessing was conducted utilising fmriprep version 21.01, based on Nipype 1.6.1 (Esteban et al. 2018; RRID:SCR_016216). First, T1-weighted images underwent intensity non-uniformity correction using N4BiasFieldCorrection (ANTs 2.3.3) and served as the anatomical reference. Skull-stripping of this anatomical reference was performed with

antsBrainExtraction and segmented via FMRIB Software Library (FSL) 6.0.5 (Jenkinson et al. 2002; Smith et al. 2004; Jenkinson et al. 2012). Spatial normalization to the MNI template version 2009c was achieved through nonlinear registration using antsRegistration (Advanced Normalisation Tools (ANTs) 2.3.3).

A custom methodology within fmriprep was employed for the preprocessing of functional images. This included: head-motion parameters relative to the BOLD reference, including transformation matrices and six rotation and translation parameters, were estimated using mcflirt (FSL 6.0.5). Functional scanning runs were slice-time corrected using 3dTshift from Analysis of Functional NeuroImages (AFNI). Co-registration of the BOLD reference to the anatomical reference with a boundary-based registration cost-function, configured with six degrees of freedom (FreeSurfer, FSL 6.0.5). Confounding time-series, such as FD, Spatial Standard Deviation of Successive Difference Images (DVARS), and region-wise global signals, were computed. Motion outliers were annotated, and the BOLD time-series were subsequently resampled into standard MNI space. All resamplings were performed in a single interpolation step using antsApplyTransforms (ANTs). Nilearn (version 0.4.2, Abraham et al. 2014) was extensively utilised within fmriprep's functional processing workflow. Further details can be found in fmriprep's documentation at (https://fmriprep.readthedocs.io/en/latest/workflows.html). The mean FD values extracted from fmriprep preprocessing were compared between low and high FER ability groups, which did not show any significant differences (W=52, p=0.695).

Following preprocessing, naturalistic data preprocessing steps were run according to established guidelines for naturalistic imaging data following the tutorial of Chang and colleagues on https://naturalisticdata.org/content/Preprocessing.html. Spatial smoothing was applied to the fMRI data using a Gaussian kernel with a FWHM of 6 mm. Identification of sudden, transient spikes in the fMRI time series was performed by detecting any data point that exceeded a predefined threshold of 3 standard deviations from the mean signal intensity. further mitigate potential sources of noise, nuisance regression was employed to remove confounding signals e.g., CSF activity and motion covariates, from the fMRI time series to

apply denoising. These steps were conducted on Jupyter Notebook (Kluyver et al. 2016) with Python version 3.10.9 (https://www.python.org/downloads/release/python-3109/).

6.2.8 Intersubject Correlation Analysis

ISC analysis was conducted as described in prior studies (Jääskeläinen et al. 2008; Kotila et al. 2021) using ISC toolbox, version 3 in MATLAB 2022b (Kauppi et al. 2014; Tohka et al. 2018). ISC computes the voxel-wise mean correlation of the BOLD time series across all pairs of subjects. Statistical inference was accomplished by a fully nonparametric voxel-wise resampling test. After computing mean ISC statistics for each voxel, a non-parametric voxel-wise bootstrap resampling test was run with 10,000,000 iterations, sampling randomly across the brain voxels for each iteration. The resulting ISC maps were thresholded at False Discovery Rate (FDR)-corrected level of $p < 0.001$. ISC maps were obtained for the whole sample, as well as for each of the groups of low and high FER ability.

ISC difference maps were computed to identify differences between the groups of low and high FER ability. Group comparison analysis was run on ISC toolbox via an unpaired studentised between-group analysis. A subject-wise permutation test was performed 25,000 times, and voxel-based and cluster extent-based correction was applied with primary cluster threshold of 0.01. Each step of the ISC analysis is shown in Figure 6.1.

To explore the functional characterisation of the differences between low and high FER ability groups in terms of brain activation synchrony, I employed the Neurosynth decoder function (Yarkoni et al. 2011). Neurosynth is described in Chapter 5, and the top 10 terms linked to the ISC results were explored.

The behavioural data analysis was run on RStudio Version 2023.06 (RStudio, PBC, Boston, MA URL http://www.rstudio.com/). The figures were created using RStudio and FSLeyes Version 1.4.6 (FSL 6.0.5).

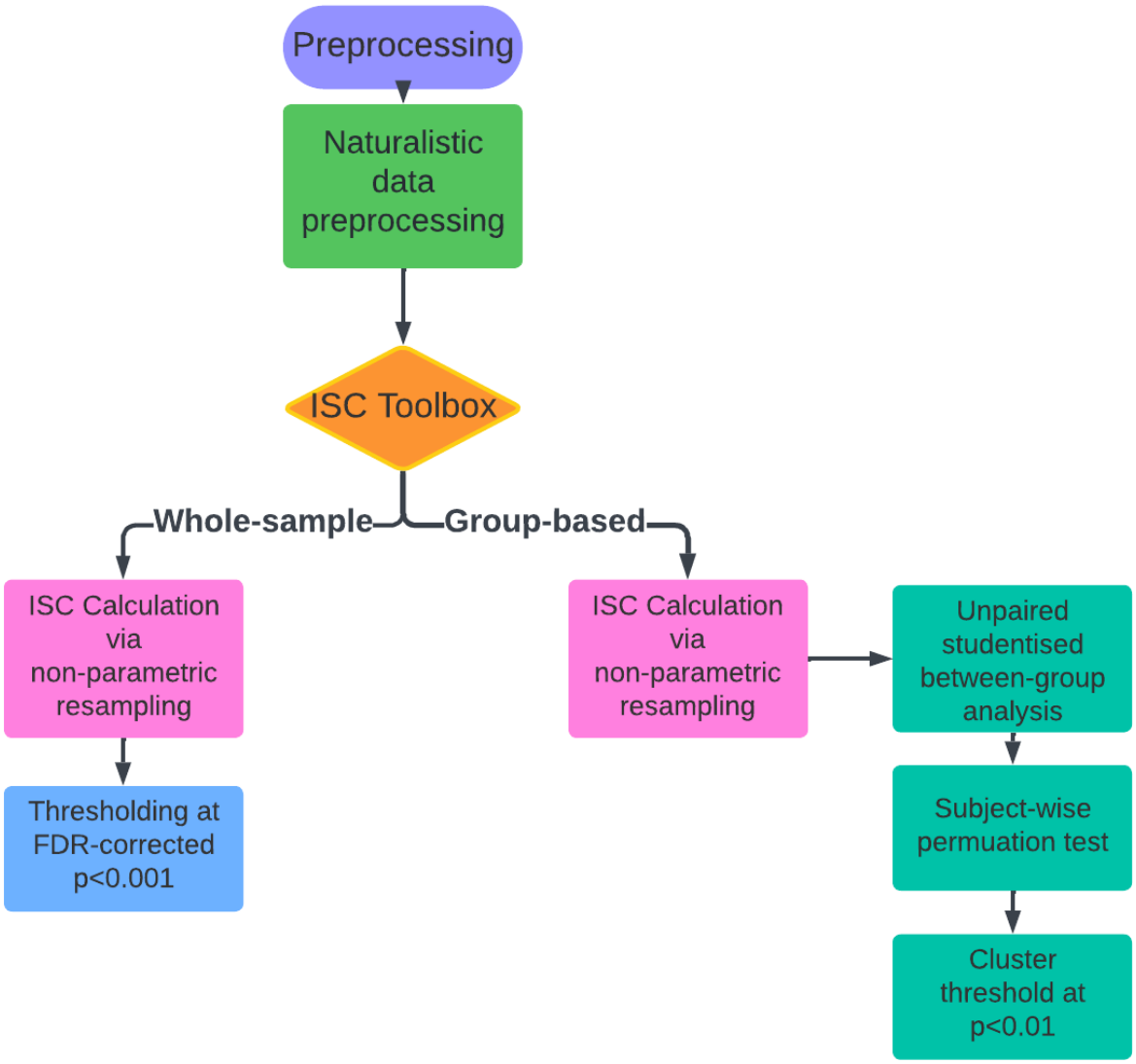

Figure 6.1: The flowchart showing the steps of intersubject correlation analyses.

6.3 Results

6.3.1 Overall ISC

Here, I computed the ISC for the whole sample while they were viewing an emotional movie clip, aiming to identify brain areas that respond synchronously whilst watching the clip across a diverse sample of children. ISC identified highly correlated activity in visual processing regions (lateral occipital cortex), executive functioning regions (superior and middle frontal

gyri), sensory processing regions (postcentral gyrus), language processing regions (inferior frontal gyrus), and cognitive control and emotion processing regions (paracingulate gyrus), as listed in Table 6.3. The brain regions with highly correlated brain activity across children in response to the emotional movie clip are depicted in Figure 6.2.

L/R	**Region**	**MNI (X)**	**MNI (Y)**	**MNI (Z)**
R	Lateral occipital cortex	54	-68	8
R	Superior frontal gyrus	14	24	66
L	Cerebellar tonsil	-14	-44	-42
R		18	-46	-46
R	Frontal pole	30	56	34
R		4	58	32
R	Lateral ventricle	24	-40	20
R	Thalamus	16	-28	2
L	Inferior frontal gyrus	-46	32	-4
R	Paracingulate gyrus/cingulate gyrus	0	38	22
R		0	48	4

Table 6.3: Regions of significant ISC in response to movie-watching across the whole-sample, p<0.001, FDR-corrected.

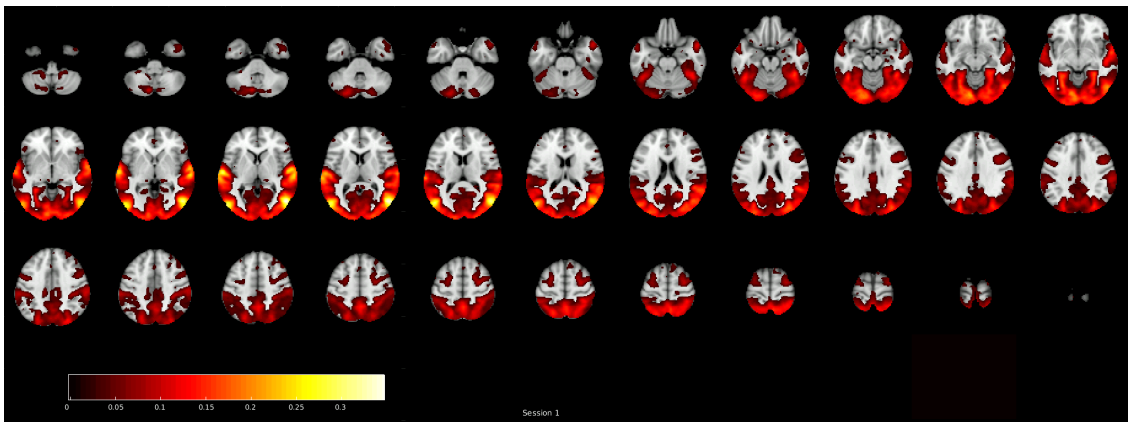

Figure 6.2: Regions with significant ISC in response to movie-watching across the whole-sample.
The colour bar shows the strength of ISCs within the brain, and lighter colours represent higher ISC. p<0.001, FDR-corrected.

6.3.2 ISC in low vs high FER ability children

I employed ISC analysis in the low and high FER ability groups separately to explore similarity in brain activity within each group while watching an emotional movie clip. ISC analysis revealed that both groups showed highly correlated brain activity in regions involved in visual and auditory processing, in addition to social cognition related regions (Figure 6.3 and Table 6.4).

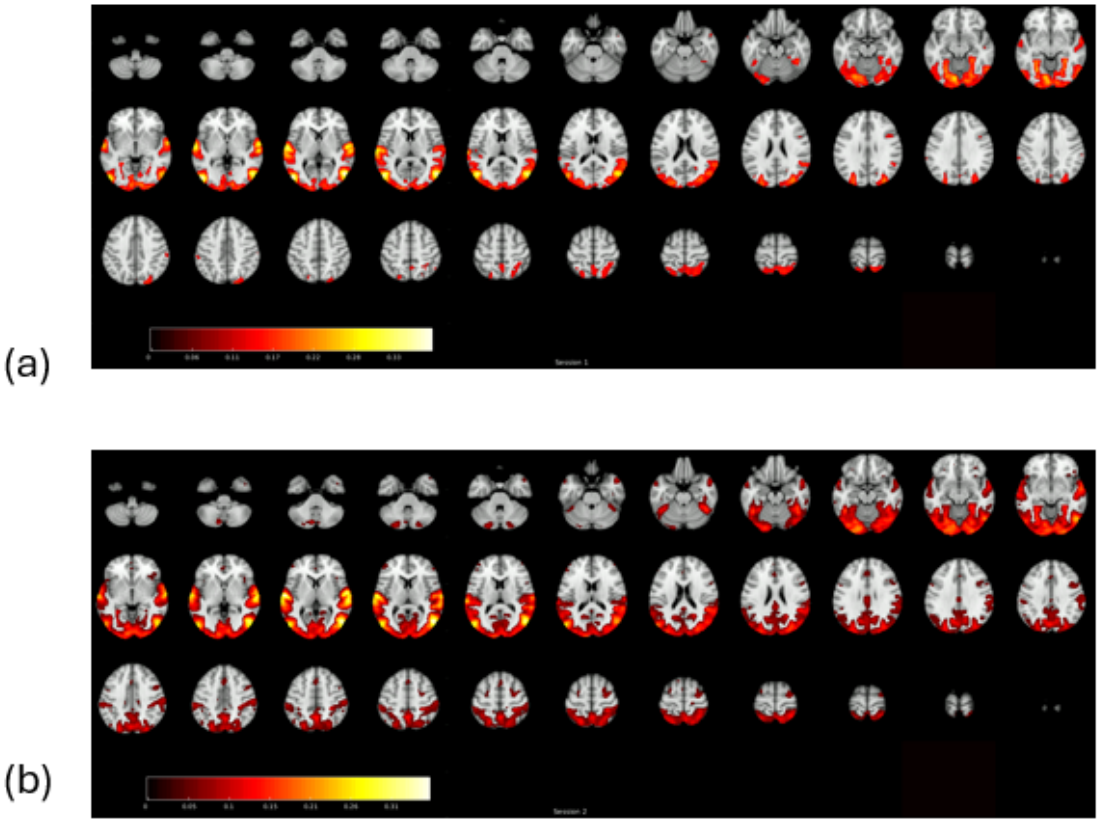

Figure 6.3: Regions with significant ISC in response to movie-watching for (a) Low FER ability group and (b) High FER ability group ($p<0.001$, FDR corrected).

In the low FER ability group, children showed the largest ISC in brain activity in the lateral occipital cortex, middle frontal gyrus, precuneus cortex (Figure 6.3). In the high FER ability group, children showed the largest ISC in the lateral occipital cortex, precentral gyrus, middle, superior, and inferior frontal gyri, paracingulate gyrus (Figure 6.3).

Contrast	L/R	Region	MNI (X)	MNI (Y)	MNI (Z)
Low FER	R	Lateral occipital cortex	54	-68	6
Ability Group	R	Middle frontal gyrus	44	12	32
		/Inferior frontal gyrus			
High FER	R	Lateral occipital cortex	54	-68	8
Ability Group	R	Precentral gyrus	32	-6	60
	R	Middle frontal gyrus	46	8	38
	R	Paracingulate gyrus	20	22	46
			2	46	46
	R	Inferior frontal gyrus	48	-52	32
	L	Cerebellum	22	-82	-32
	L	Frontal pole	-44	48	8
	L	Superior frontal gyrus	-26	0	68

Table 6.4: Regions with significant ISC in response to movie-watching in low FER ability and high FER ability groups, $p<0.001$, FDR-corrected.

When directly comparing the two groups, the low FER ability group exhibited greater ISC in inferior parietal lobe, superior frontal, and medial frontal gyrus, relative to the high FER ability group. Conversely, the high FER ability group had greater ISC in ventromedial prefrontal cortex relative to the low FER ability group. Significant group differences in ISC are depicted in Figure 6.4 and listed in Table 6.5.

Contrast	L/R	Region	MNI (X)	MNI (Y)	MNI (Z)
Low FER Ability >	R	Inferior parietal lobe	50	-54	52
High FER Ability	L	Frontal pole	-30	66	2
	L	Medial frontal gyrus	-16	-8	48
High FER Ability >	R	Ventromedial prefrontal	2	42	-16
Low FER Ability		cortex			

Table 6.5: Significant differences in ISC between low FER ability and high FER ability groups during movie watching, $p<0.001$, FDR-corrected.

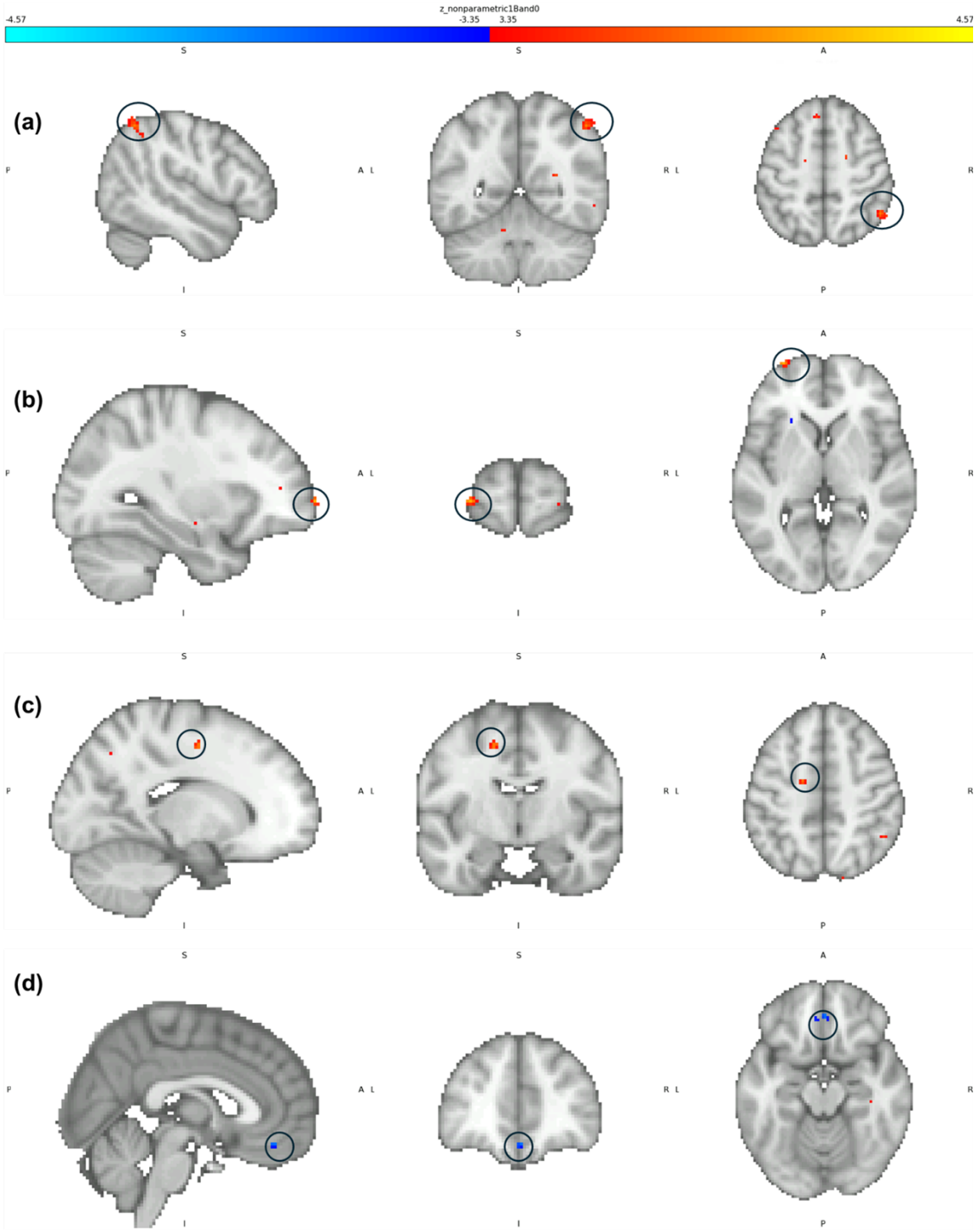

Figure 6.4: Regions with significant differences in ISC between FER ability groups. Hot colours depict brain regions with greater ISC in low FER ability group compared to high FER ability group, whereas cool colours depict brain regions with greater ISC in high FER ability group compared to low FER ability group (a) Inferior parietal lobe. (b) Frontal pole. (c) Medial frontal gyrus. (d) Ventromedial prefrontal cortex. Circles identify each of the key clusters. $p<0.05$, FDR corrected.

6.3.3 Functional Decoding via NeuroSynth

The NeuroSynth decoder was used to explore similarities between meta-analytic functional maps generated by the Neurosynth database and ISC activation patterns for the contrasts Low FER ability children > High FER ability children, and High FER ability > Low FER ability. Functional terms associated with the ISC maps Low FER ability > High FER ability included "visual", "navigation" and "place", whereas "pain", "default mode", and "response inhibition", amongst others, were associated with the High FER ability > Low FER ability ISC maps (Figure 6.5).

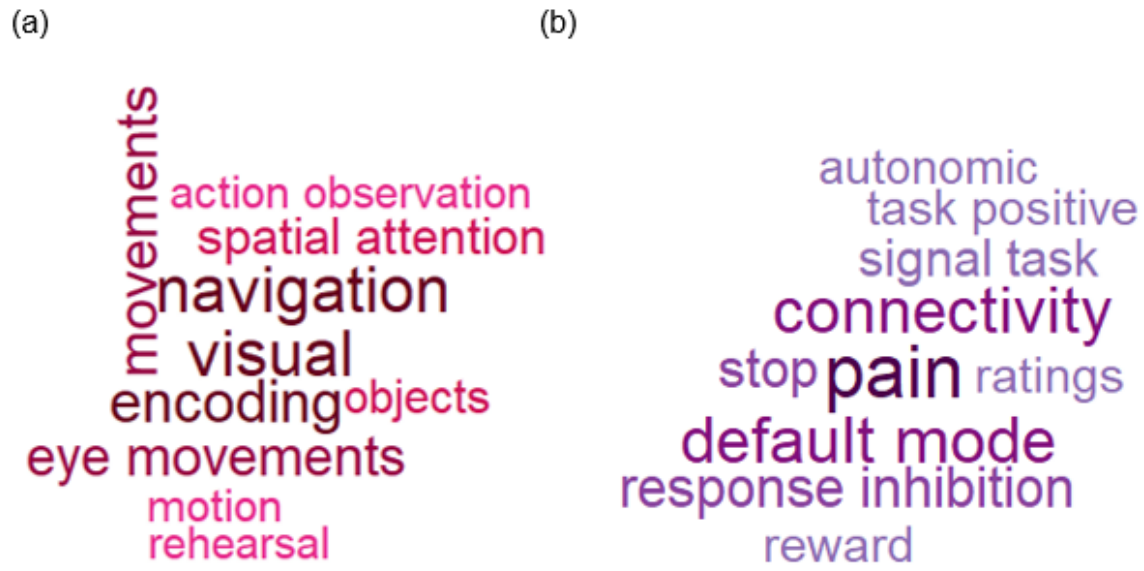

Figure 6.5: Functional decoding retrieved from NeuroSynth of ISC differences between groups. (a) Correlation word cloud of the ISC difference map (Low FER ability > High FER ability). (b) Correlation word cloud of the ISC difference map (High FER ability > Low FER ability). The size of the font represents the strength of the correlation between the ISC difference maps and term-based meta-analysis maps generated by Neurosynth. $p<0.05$, FDR corrected.

6.4 Discussion

This chapter underscores the nuanced differences in brain activity synchronisation across children with varying levels of FER abilities in response to an emotional movie. The results identified significant synchronisation of brain activity across a sample of children with

varying levels of facial emotion recognition accuracy, as well as distinct patterns of brain synchronisation between children with lower or higher FER ability. Notably, the sample as a whole exhibited the highest brain synchrony in regions associated with visual, auditory processing, and social cognition, irrespective of their FER abilities. However, examination of group differences revealed intriguing findings; children with lower FER ability exhibited elevated brain synchronisation in the inferior parietal lobe, superior frontal, and medial frontal gyrus, contrasting with the heightened synchronisation observed in the ventromedial prefrontal cortex among children with higher FER ability. Notably, the group differences in brain synchronisation were related to functional domains such as visual processing, movement, action observation in low FER ability group, whereas they were pain perception, and default mode network in high FER ability group. These findings suggest that there are differences in the overall brain activity patterns of children, related to their facial expression recognition ability but regardless of their wider behavioural profile, whilst watching an emotional movie clip, as well as common patterns of synchrony that are consistent across all children.

The patterns of brain activation synchrony across the entire sample, are consistent with previous research findings of brain synchronisation in response to the same movie clip (Camacho, Balser, et al. 2023; Gruskin et al. 2020; Lyons et al. 2020; Ou et al. 2022). These studies used data from the Child Mind Institute's Healthy Brain Network, a large, multi-site study of children and adolescents (available at: `https://fcon_1000.projects.nitrc.org/indi/cmi_healthy_brain_network/index.html`). This initiative encompasses a high-risk community sample of children and adolescents, recruited based on concerns expressed by their families, teachers, or local care providers regarding potential psychiatric symptoms. They found brain activation synchrony of areas involved in visual processing, auditory processing, default mode, and attention networks similar to findings of the current study. Despite the sample size of 22 in the current analysis compared to over 500 participants in the previous studies, the current study nevertheless identified brain synchronisation of similar regions across children. This provides support to the claim by Pajula & Tohka (2016) that a minimum

of 20 participants are adequate for detecting significant brain synchronisation using ISC.

Both the low and high FER ability groups showed the highest brain activity synchronisation in visual and auditory processing regions, which overlap with previous studies (Camacho, Balser, et al. 2023; Gruskin et al. 2020; Lyons et al. 2020; Ou et al. 2022) using the same emotional movie. This suggests a common baseline of brain synchrony in these sensory regions across different levels of FER ability.

However, different patterns in brain activation synchrony emerged between these groups. Children with better FER abilities exhibited heightened brain activation synchrony across larger and more widespread regions of the brain, particularly also extending to frontal areas. This may indicate a more extensive network of brain regions involved in processing emotional information, suggesting a potentially more nuanced or elaborate emotional processing mechanisms in children with better FER abilities. The different patterns were apparent after statistical analysis that the higher brain activation synchrony observed in the ventromedial prefrontal cortex amongst these children highlights this region's potential significance in emotion processing. Previous research has linked this brain region to decision-making processes, where it integrates various information sources to guide choices and behaviours (Fellows & Farah 2007; Hiser & Koenigs 2018). It also serves as a central hub for emotion processing and regulation, forming network connections with regions like the amygdala, cingulate cortex, hippocampus, which are essential for social cognition (Davidson 2002; Heberlein et al. 2008; Hiser & Koenigs 2018; Winecoff et al. 2013).

Conversely, children with lower FER ability demonstrated heightened brain activation synchrony in regions including inferior parietal lobe, frontal pole, and medial frontal gyrus, relative to children with higher FER abilities. These significantly differing regions with synchronous activity during movie watching hint at differential processing mechanisms in children with lower FER abilities. A closer examination of these regions reveals their involvement in various social and cognitive abilities. For example, the inferior parietal lobe plays an important role in numerous domains, including attention, language, and social cognition,

covering both low-level cognitive processing (e.g., attention), and high-level processing (e.g., language, social cognition). In particular, the right inferior parietal lobe is associated with attentional processing, whereas its role in perspective taking involves bilateral inferior parietal lobe (V. I. Müller et al. 2013; Numssen et al. 2021). This finding suggests that children with lower FER abilities may rely more heavily on attentional networks, potentially as a compensatory mechanism. Moreover, the frontal lobe is known for its role in executive functioning and emotion regulation (Bramson et al. 2019; Roelofs et al. 2023; Volman et al. 2011). Similarly, the medial frontal gyrus is involved in self-referential processing, cognitive control, and the perception of pain and negative emotions (Casale et al. 2017; Kragel et al. 2018). The increased synchrony in these regions among children with lower FER abilities suggests significant differences in how they process social interactions and emotions presented during movie watching. This may indicate a compensatory mechanism, or alternative neural processes for handling emotional content compared to children with higher FER abilities. Overall, the greater brain activation synchrony of these regions hint at distinct processing mechanisms in children with lower FER abilities whilst watching an emotional movie clip, although further research is warranted to investigate their specific nature.

Expanding on the insights of Chapter 5, which identified a shared network of gray matter covariance among children with varying levels of facial expression recognition abilities, the present chapter delves further into understanding the neural mechanisms underlying functional differences in emotion processing. The structural network of gray matter covariance, associated with diminished negative facial expression recognition abilities, revealed involvement of regions including inferior parietal lobe, middle temporal gyrus, inferior and middle frontal gyrus. Analysing shared synchrony in response to an emotional movie within a subsample of these children, I observed that children with lower FER abilities show a similar pattern of inferior parietal lobe in both structural and functional imaging analyses. Together, these findings underscore some consistency across both structural and functional analyses, emphasising the distinct involvement of the inferior parietal lobe as a key region exhibiting both structural and

functional differences in children with lower facial expression recognition abilities. Despite the inferior parietal lobe primarily being characterised in its role in motor and movement-related functions, its involvement in social cognition, such as perspective taking, self-perception has also been shown (Igelström & Graziano 2017). Moreover, it serves as a key hub of the default mode network and exhibits connections with multiple regions involved in motor processing, movement, action observation, and social cognition (Braga et al. 2020; Numssen et al. 2021). Various studies have also highlighted the role of inferior parietal lobe in emotion processing, including facial expression processing (Adolphs et al. 1996; Sarkheil et al. 2013; Krautheim et al. 2019), emotional body expression processing (Engelen et al. 2015), and affective theory-of-mind (Mier et al. 2010). The findings from Chapter 5, along with the aforementioned studies, underscore the significance of the inferior parietal lobe in emotion processing, as revealed through overlapping structural and functional differences found here. Future research should focus on the exact role of the inferior parietal lobe in emotion processing, particularly in children with a broad range of emotion recognition abilities.

6.4.1 Strengths and Limitations

The present study boasts inherent strengths through its transdiagnostic approach, underscoring its capacity to offer novel insights into shared brain synchrony in response to an emotional movie, particularly in the context of children with various levels of emotional, cognitive, and/or behavioural difficulties. In alignment with the rationale established in the preceding chapter, I adopted a methodology aimed at elucidating similarities and differences in the underlying brain activation synchrony linked to facial expression recognition abilities in a diverse sample of children. The examination of brain activation synchrony in response to emotional stimuli in these children enabled the detection of commonalities in neural responses within a sample of children with varying levels of facial emotion processing. Subsequently, group comparisons allowed for the detection of differences in brain activation synchrony relating to emotion processing in children characterised by lower and higher facial expression

recognition abilities.

Notably, it is important to highlight that these delineations into low and high FER ability groups were agnostic to the source of recruitment, encompassing both children who were referred to the NDAU, as well as children from the community. This deliberate inclusivity aligns with the RDoC framework's transdiagnostic dimensional approach, which captures a spectrum of facial expression recognition abilities, regardless of emotional, cognitive, and/or behavioural difficulties among participants. In contrast to previous studies using the same emotional movie stimuli among high-risk children and adolescents, which primarily focused on comparing psychiatric traits like autism, depression, and social anxiety to neurotypical peers, the present study adopts a novel, RDoC-aligned approach. Rather than relying on traditional diagnostic categories, this study focuses on children exhibiting a continuum of FER abilities. This shift allows for a more nuanced investigation into the relationship between neural mechanisms and emotion processing abilities, reducing the potential for bias introduced by characteristics associated with specific diagnoses. By emphasising a dimensional approach rooted in the Systems for Social Processes domain of the RDoC, the current study highlights the link between facial emotion recognition abilities and brain activation patterns during social interactions, independent of behavioural profile.

The use of ISC analyses enables the utilisation of naturalistic stimuli, e.g., movies and narratives. This approach enhances the generalisability and ecological validity of the findings by allowing for the exploration of complex, emotional, and dynamic stimuli (Nastase et al. 2019; Saarimäki 2021). Indeed, the utilisation of an emotional movie in this study heightened the likelihood of capturing neural responses reflective of real-world socioemotional processing.

However, despite the valuable perspectives offered by the findings, it is essential to address certain limitations in the study. Firstly, the sample size of 22 participants, while falling within the range necessary for reproducible and reliable analysis, as suggested by prior research (Pajula & Tohka 2016), is still a relatively small sample, particularly when considering the variability inherent in a diverse sample of children. Furthermore, the group analyses by

FER ability resulted in even smaller samples being compared with one another. While the current study demonstrated similarities to previous findings in the literature, a replication of the current study with a larger sample size would be advantageous. Secondly, ISC analyses inherently have their own limitations as well. ISC reflects shared synchrony of brain activity across individuals and does not provide insight into individual differences or idiosyncratic patterns of brain activation or deactivation. Consequently, ISC may overlook individual differences, which may be of particular interest when studying a diverse group of children, with a range of behavioural profiles.

6.5 Conclusion

This chapter explored the shared brain activation synchrony among children with varying levels of emotional and behavioural difficulties, with a specific focus on the role of facial expression recognition abilities in brain activation synchrony during movie-watching. I demonstrated that despite the diversity in their behavioural profiles, these children exhibited similar overall synchronised brain activity in response to emotional stimuli, similar to findings observed among their peers in prior studies. Moreover, distinct patterns of synchronised brain activity emerged when comparing children with lower and higher FER abilities, including in inferior parietal lobe, frontal pole, medial frontal gyrus, and ventromedial prefrontal cortex. These regions are integral to functions such as attention, language, social cognition, and emotion regulation. The identification of these distinct neural signatures sheds light on the nuanced nature of emotion processing across a developmental population, offering valuable insights into social cognition and emotion processing.

Chapter 7

General Discussion

7.1 Summary of Key Findings

This thesis embarked on a journey to explore facial expression processing across both behavioural and neural dimensions. In Chapter 3, I delved into the facial and body expression recognition abilities of neurotypical children shedding light on how contextual cues influence their facial expression judgments. Typically developing children were found to be biased by body context during their facial expression recognition judgements, in addition this bias was linked to their proficiency in recognising isolated facial expressions. Building upon this foundation, Chapter 4, scrutinized these abilities and mechanisms within children with emotional, cognitive, and/or behavioral difficulties, juxtaposed against their neurotypical peers. Interestingly, the findings unveiled shared underlying mechanisms in contextual cue integration among at-risk children, echoing the patterns observed in their neurotypical peers. Specifically, at-risk children exhibited a bias towards body context during their facial expression recognition judgements, as well as showing an association between the strength of the bias and proficiency in isolated facial expression recognition.

Broadening the scope further, Chapter 5 explored the structural markers of facial expression recognition across children displaying varying degrees of emotional, cognitive, and/or

behavioural difficulties. This exploration uncovered a network of gray matter covariance, highlighting specific regions like the inferior parietal lobule, middle temporal gyrus, insula, and fusiform gyrus, which were linked to facial expression recognition abilities across at-risk sample of children. Specifically, children with lower facial expression recognition abilities contributed more to this network of gray matter covariation which had increased gray matter volume in the inferior parietal lobule, middle temporal gyrus, and decreased gray matter volume in the insula and fusiform gyrus. Such revelations underscore the potential of a transdiagnostic approach in identifying common structural markers of facial expression recognition.

In Chapter 6, the focus shifted towards investigating brain activation synchrony in response to emotional stimuli among children with varying levels of facial expression recognition abilities. This study unveiled intriguing distinctions in synchronized brain activity between children with low and high facial expression recognition capabilities. Children with high facial expression recognition abilities showed higher synchronisation in the ventromedial prefrontal cortex, whilst children with low facial expression recognition abilities showed higher synchronisation within regions of the inferior parietal lobe, frontal pole, and medial frontal gyrus.

In summary, this thesis navigated the complex realm of facial expression recognition, at the behavioural and neural level, offering insight into emotional processing among children with diverse developmental trajectories.

7.2 Emotion Processing in Children

7.2.1 How Children Process Facial and Body Expressions

Understanding how children recognise, and process emotions is essential for grasping the nuances of social cognition throughout development. Emotion research has shown that verbal and non-verbal cues -such as facial expressions, body language, voice, contextual background- are instrumental in identifying emotions (Herba & Phillips 2004; Chronaki 2021;

Parker et al. 2013). I contributed to this field by examining both isolated emotional cues and their integration in neurotypical (Chapter 3) and at-risk children (Chapter 4). These findings provided insight into mechanisms underlying the influence of contextual cues in facial expression perception, highlighting both how these mechanisms manifest and reflect shared properties across different populations.

Facial expressions have been the primary focus of emotion recognition studies, and extensive literature shows that children become better at recognising facial expressions as they age, with different emotion categories displaying distinct developmental patterns (Parker et al. 2013; Widen 2013). For instance, happy facial expressions have been found to be accurately identified from an early age (Barisnikov et al. 2021; Herba & Phillips 2004). Although other basic emotions such as anger, sadness, fear have varied developmental trajectories across studies, they are generally recognised as negative emotions early in development, with anger and sadness being differentiated by the age of six (Lawrence et al. 2015; Watling & Damaskinou 2018). In Chapter 3, I replicated this established literature in typically developing children and demonstrated a trend of improving facial expression recognition performance with age among children aged 4 to 10. Notably, children showed the greatest proficiency in recognising happy facial expressions, while their ability to identify angry, sad, and fearful facial expressions was comparable. Subsequently, in Chapter 4, I investigated how these patterns manifest in at-risk children. My findings revealed that at-risk children aged 4 to 7 exhibited more difficulties in facial expression recognition compared to their neurotypical peers, with the most pronounced difficulties observed in recognising angry and fearful facial expressions. This aligns with existing research on the developmental trajectories of anger and fear recognition, as well as their association with various neurodevelopmental conditions such as conduct problems, callous-unemotional traits, and ADHD (Martin-Key et al. 2018; Levantini et al. 2022; Deters et al. 2020; Aspan et al. 2014; Airdrie et al. 2018). Thus, the impaired performance of at-risk children in Chapter 4 is consistent with the existing literature on children with diagnosed neurodivergent conditions. Here, I provide evidence that these

difficulties in facial expression recognition extend to children with varying levels of emotional, cognitive, and/or behavioural difficulties, even in the absence of a clinical diagnosis.

It is important to highlight the differences in developmental trajectories of various facial emotion categories, and how this influenced a focus on negative facial expressions in the later chapters of thesis, which included older children. Notably, happy facial expressions are recognised earlier in development compared to other emotions (Barisnikov et al. 2021; Herba & Phillips 2004; Lawrence et al. 2015). In Chapter 3 and 4, younger children aged 4 to 10 showed high accuracy in recognising happy facial expressions – close to ceiling for typically developing children and NDAU children. Similarly, in Chapter 5 and 6, the overall sample of at-risk children aged 7 to 12 also showed ceiling effects in recognising happy facial expressions. These findings indicate that children can easily recognise happy facial expressions from an early age, even those with high levels of emotional, cognitive, and/or behavioural difficulties. Consequently, the focus shifted to the recognition of negative facial expressions, particularly in the later chapters, where the sample consisted of older children.

Another essential reason for this focus on negative facial expression recognition is the extensive research showing that children with neurodevelopmental conditions often struggle to recognise negative facial expressions (Blair et al. 2018; Martin-Key et al. 2021; Collin et al. 2013). For instance, children with conduct disorder have lower accuracy in recognising fearful facial expressions compared to their neurotypical peers (Blair et al. 2018; Fairchild et al. 2013). Likewise, children with autism find it challenging to recognise negative facial expressions, such as fear, anger, and sadness (Vandewouw et al. 2020; Yeung 2022; Wallace et al. 2008). The existing literature indicates that children with neurodevelopmental conditions have difficulties in recognising negative facial expressions, which may involve differences in emotion categories. Therefore, in studying a sample with varying emotional, cognitive and/or behavioural difficulties, and shifting the focus to negative facial expressions, it was important to focus on negative facial expressions rather than focusing on specific emotion categories.

Recently, there has been growing interest in body expressions within emotion processing

research. The development of body expression recognition has been found to improve with age, similar to facial expression recognition (Parker et al. 2013; Wu et al. 2022; N. L. Nelson & Russell 2011). However, developmental trajectories of body emotion categories are not yet well-established due to the relatively new nature of this research. In Chapter 3, older children exhibited better performance in body expression recognition than younger children. Notably, fearful, and angry body expressions were the best recognised, whereas happy and sad body expressions proved to be more challenging for children to identify across all ages. By exploring body expression recognition in typically developing children, I contributed to the growing literature on emotion processing from bodily cues. Chapter 4 further advanced our understanding by examining body expression recognition across at-risk children and their neurotypical peers. To the best of my knowledge, this is the first study to explore body expression recognition in children with varying levels of emotional, cognitive, and/or behavioural difficulties using a transdiagnostic approach. I found that at-risk children do not differ in their body expression recognition abilities compared to their neurotypical peers. This suggests that their difficulties in emotion recognition from faces do not extend to emotions expressed by body posture.

Previous research showed that individuals with neurodevelopmental conditions, such as conduct disorder (Martin-Key et al. 2021), autism (Metcalfe et al. 2019; Philip et al. 2010), generally exhibit lower accuracy in both static and dynamic face and body recognition. Conversely, a study on autistic adults found no difference in recognising static faces and dynamic bodies compared to neurotypical peers (Actis-Grosso et al. 2015). The findings in Chapter 4 indicated that children with emotional, cognitive, and/or behavioural difficulties perform similarly to typically developing children in recognising isolated body emotions. This suggests that despite their difficulties, their ability to interpret body expressions for emotional cues is not significantly impaired. Among the mixed findings in the literature, this thesis supports the notion that children with emotional, cognitive, and/or behavioral difficulties may retain intact body expression recognition abilities. However, this finding underscores

the need for further research to clarify the complex patterns of emotion recognition from body expressions within populations of neurodevelopmental conditions. Future studies should consider larger sample sizes and varying intensity levels of body expressions. Additionally, it is important to investigate whether emotion recognition from other contextual cues, such as voice and visual background, is impaired in at-risk populations.

It is well-established that neurotypical populations show improvement in emotion recognition through voice with age (N. L. Nelson & Russell 2011; García-Guerrero et al. 2022; Rigoulot & Pell 2014). However, results are more inconsistent among neurodevelopmental conditions. For instance, adolescents exhibiting high levels of psychopathic traits display lower facial expression recognition abilities, whereas their ability to recognise emotion from voices was negatively associated with only levels of affective psychopathic traits (Gillen et al. 2018). Likewise, autistic individuals show decreased performance in voice recognition compared to their neurotypical peers (Philip et al. 2010). Löytömäki, Ohtonen, Laakso, & Huttunen (2020) found that children with autism, ADHD, or developmental language disorder exhibit lower accuracy in voice recognition compared to neurotypicals, without significant differences among these neurodevelopmental groups. The findings on the influence of body expressions in this thesis showed that neurodevelopmental populations exhibit a specific difficulty in facial expression recognition whereas their body expression recognition is intact. Given the shared difficulties in voice recognition and facial expression recognition across neurodevelopmental conditions, it is plausible that shared mechanisms underlie the impaired processing of facial and vocal cues, whereas the representation of body cues might involve different mechanisms. Hence, different contextual modalities of emotion processing could reveal themselves in distinct and specific ways. Further research should focus on emotion recognition abilities across various stimulus types (e.g., face, body, voice) and developmental stages in neurodevelopmental groups.

7.2.2 How Children Integrate Facial and Body Expression

Building upon the recognition of isolated emotion cues, I examined how the presence of body expressions influences children's performance in facial expression recognition, and what factors drive this influence across neurotypical (Chapter 3) and at-risk children (Chapter 4). Studies in adults have demonstrated that congruent body cues enhance facial expression recognition performance, while incongruent cues impair it (Karaaslan et al. 2020; Gunes & Piccardi 2006). However, research on this topic in developmental populations is limited. I found that typically developing children exhibit adult-like performance, showing decreased performance in facial expression recognition when accompanied by incongruent body cues compared to congruent body cues in Chapter 3, consistent with the existing literature (Mondloch 2012; Mondloch, Horner, & Mian 2013). Additionally, I demonstrated for the first time that neurotypical children benefit form congruent body expressions , leading to improved facial expression recognition compared to isolated facial expression recognition. These findings contribute to our understanding of how body context influences facial expression recognition in neurotypical children.

Furthermore, in Chapter 4, I looked at the same mechanisms in at-risk children and their neurotypical peers. Similar to their neurotypical peers, at-risk children exhibited better facial expression recognition performance in the presence of congruent body expressions compared to incongruent ones during their facial expression recognition judgements. Interestingly, at-risk children showed an improvement in facial expression recognition when presented with congruent body expression compared to isolated facial expressions. This suggests that at-risk children with difficulties in facial expression recognition might benefit from having congruent emotional cues to support facial expression recognition. Whether this extends to congruent emotional cues from other modalities, e.g. voice, situational context, etc, remains to be seen. Nevertheless it remains a potentially promising avenue for future intervention-focused research.

Only few recent studies have shed light on the influence of body expressions in facial

expression recognition across atypical neurodevelopmental populations. Santamaría-García et al. (2019) and Pino et al. (2019) revealed that young offenders display diminished facial expression recognition accuracy when presented with incongruent body expressions compared to congruent ones. Here, I presented the first findings on the influence of body context on facial expression judgements across at-risk children. It reveals a consistent pattern of reduced performance in the presence of incongruent cues, aligning with prior research within neurodevelopmental populations. Interestingly, this tendency towards body cues persists despite these children's impaired facial expression recognition abilities, while their ability to recognise body expressions remains intact. In their work, Santamaría-García et al. (2019) and Pino et al. 2019 did not explore isolated facial expression abilities of their adolescent populations. Therefore, this thesis provides evidence that at-risk children, despite struggling with facial expression recognition, still demonstrate the influence of body context in their facial expression judgements, similar to neurotypical peers. These findings suggest that at-risk children may not vary substantially in their integration of body expressions with facial expressions. Rather, they potentially encounter specific difficulties in facial expression recognition. This emphasises the importance of considering individual differences in facial expression recognition in the presence of body cues.

In the previous chapters of this thesis, I have gained insight into the similarities in the mechanisms underlying the integration of body posture with facial expression information between children with emotional, cognitive, and/or behavioral difficulties and their neurotypical peers. Chapter 4, in particular, demonstrated that both groups of children are influenced by body context during facial expression recognition, with the extent of this influence depending on their proficiency in isolated facial expression recognition abilities. Remarkably, this phenomenon persists despite the significantly lower facial expression recognition abilities observed in at-risk children, as outlined in Chapter 4. These findings suggest that certain aspects of emotion processing may remain consistent across diverse populations. Limited research has been conducted on this driving mechanism of isolated facial expression

recognition on the extent of the body context influence. Studies have shown that individuals with higher performance in isolated facial expression recognition are less likely to be biased towards incongruent body expressions during their facial expression recognition judgments, as observed among typically developing children and adolescents (Ward et al. 2023) and autistic adults (Brewer et al. 2017). The findings in Chapter 3 are consistent with these studies, and focus on a narrower age range of children, those aged 4 to 10, compared to Ward et al. (2023) which focused on children aged 8 to 18. Similarly, the results in Chapter 4 suggest a similar mechanism driving the influence of body context on facial expression recognition in at-risk children for the first time, providing evidence for common underlying mechanisms of integration of emotion signals in children with varying levels of facial expression recognition difficulties.

Given the influence of body context on facial expression recognition (Aviezer et al. 2012; Mondloch 2012), further research should investigate the reciprocal relationship between facial expressions and body expression recognition. This thesis explored how body expressions influence facial expression recognition. However, the reverse influence -how facial expressions influence body expression recognition-remains unexplored. Lecker, Dotsch, Bijlstra, & Aviezer (2020) found that adults exhibit an influence of facial expressions on body expression recognition, but that the effect of body context on facial expression is larger than the effect of face context on body expression. There is a notable lack of studies establishing this bi-directional relationship in neurodevelopmental and at-risk populations. In order to fully address integration mechanisms of face and body emotion, future research should investigate the influence of face context on body posture recognition in order to assess whether similar principles govern integration of contextual information for body emotion recognition.

Body cues are not the sole source of contextual information for interpreting facial expressions in daily interactions. Other contextual cues include, but are not limited to, voice, and situational context. The findings of Chapter 3 and 4 raise the question of whether the mechanisms of contextual influence reported here might extend to other contextual cues

(Barrett et al. 2007; Matsumoto & Hwang 2010; Wieser & Brosch 2012). Irwantoro, Lennon, Mareschal, & Ismail (2022) explored the influence of context on facial expression recognition by using audiovisual, dynamic cues depicting happy or angry video clips. They found that among neurotypical young adults, audiovisual, dynamic context improved facial expression recognition compared to uninformative context (e.g., noise). Additionally, they observed lower accuracy in facial expression recognition after participants experienced an incongruent context compared to an uninformative one. Theurel et al. (2016) showed that typically developing children's facial expression recognition performance improves when visual context is provided compared to no context. This is in line with my findings, which demonstrated that children's performance in facial expression recognition improves with congruent body cues and diminishes with incongruent cues (Chapters 3 and 4) and suggests that congruent contextual cues from other modalities might support facial expression recognition.

However, there is some evidence to suggest certain contextual cues may be processed differently in neurodivergent groups relative to typically developing children. For instance, Murray et al. (2019) conducted an emotion labelling task with children with and without intellectual disabilities using different types of stimuli: line drawings, photographs with limited context, and photographs with high context. Typically developing children performed better overall than children with intellectual disabilities, but they performed worst in the line drawing condition, whereas children with intellectual disabilities performed best in this condition. This study shows that different types of contextual cues might have differential effects on at-risk populations. Ortega, Chen, & Whitney (2023) conducted a study investigating emotion processing in individuals with different levels of autistic traits in the presence of contextual cues. They found that impairments in facial expression recognition were observed among individuals with higher autistic traits, and these difficulties extended to contextual cues similar to the findings in Chapter 4 regarding at-risk children.

While the children studied in this thesis did not have a diagnosis, the level of emotional, cognitive and behavioural difficulties they exhibit make it likely that many of them will

transition to a diagnosed condition with time. Although beyond the scope of this thesis, it would be important to examine changes in facial expression recognition among these at-risk children over time, particularly focusing on which children are more likely to improve and achieve neurotypical performance levels, and which children may not improve or even decline, potentially leading to one or more clinical diagnoses. Understanding the underlying mechanisms of these trajectories could provide valuable insights into what drives these differing outcomes. Factors such as family dynamics, school environment, and individual differences significantly influence children's resilience (Zolkoski & Bullock 2012; Bush & Roubinov 2021). Additionally, biological factors may impact a child's resilience. Identifying these environmental and biological factors is essential for revealing the diverse trajectories of emotion processing in at-risk populations. Future longitudinal studies employing transdiagnostic approaches would be invaluable in uncovering the risk and resilience factors that impact the progression or worsening of emotion processing abilities.

Overall, this thesis has made significant contributions in understanding how children process emotions, particularly from facial and body expressions. By examining both isolated emotional cues and their integration in both neurotypical and at-risk children, I provided new insight into the mechanisms underlying emotion processing across different populations. Importantly, this research has extended our understanding to at-risk populations rather than focusing on clinical diagnoses. I demonstrated that while at-risk children may exhibit impaired facial expression recognition abilities, they benefit from congruent body expressions. Additionally, despite poorer facial expression recognition abilities, these at-risk children exhibit similar principles governing the integration of body posture in their facial expression judgements. Overall, these contributions have expanded our knowledge of emotion processing in at-risk children, paving the way for future research to explore these mechanisms further and develop interventions tailored to individual needs.

7.3 Emotion Processing in Brain

Face perception has been extensively studied in neuroimaging research, with a network of brain regions showing specificity for faces, including the FFA alongside the posterior STS and OFA (Haxby & Gobbini 2011; Duchaine & Yovel 2015). Similarly, research has suggested that there are several regions which show specificity for body perception including the Fusiform Body Area (FBA) and the Extrastriate Body Area (EBA) (Ramsey 2018; B. Li et al. 2023). While these findings highlight specific brain regions involved in processing faces and bodies, understanding the dynamics of emotion processing, is more complex. For instance, facial expression perception engages core face perception regions, but also engages a broader network that includes regions within the limbic system, prefrontal cortex, and mirror neuron system, illustrating the interconnected nature of facial expression recognition with broader emotion processing networks (P. Xu et al. 2021; Johnston et al. 2013; M. Liu et al. 2021).

To increase our understanding of how the brain processes emotions, it is essential to consider both the structural and functional networks that facilitate communication across different regions and networks. Research on emotion processing, particularly in the realm of facial expression recognition, has predominantly been investigated through functional imaging studies. For instance, the amygdala, prefrontal cortex, and other areas work in concert to decode and identify emotional stimuli (Loughead et al. 2008; P. Xu et al. 2021; Hadjikhani & Gelder 2003). Therefore, focusing solely on region-specific approaches might overlook the broader neural networks that are crucial for emotion processing in the brain.

Previous structural neuroimaging studies have examined specific neurodevelopmental conditions such as autism or conduct disorder and associated structural brain differences, potentially characterising their emotion processing difficulties. For example, M. X. Xu & Ju (2023) reported increased gray matter volume in hippocampus and temporal regions among children with autism compared to typically developing children. Similarly, Fairchild et al. (2011) found decreased gray matter volume in the amygdala in adolescents with conduct disorder

compared to their neurotypical peers. However, these studies often failed to directly link these neural markers to facial emotion processing, which limits our understanding of how changes in brain structure might contribute to facial emotion processing in at-risk populations.

On the other hand, functional imaging studies have explored neural differences in facial emotion processing between individuals with neurodevelopmental conditions and those who are typically developing. A meta-analysis by Aoki, Cortese, & Tansella (2015) revealed that individuals with autism exhibit atypical brain responses, such as increased activity in the thalamus, caudate, amygdala and precuneus, and decreased activity in the hypothalamus during facial emotion processing compared to neurotypical peers. Additionally, Berluti, Ploe, & Marsh (2023) reviewed emotion processing in youth with conduct problems and found reduced activation in the motor and frontal regions, as well as the amygdala, when viewing emotional faces. These studies highlight the distributed and widespread networks involved in facial emotion processing within neurodevelopmental conditions.

To bridge the gap between structural and functional imaging findings, I aimed to establish a direct connection between facial emotion processing and its neural markers by building upon existing evidence. Specifically, I investigated the structural network and brain activation synchrony in children with varying levels of facial expression recognition abilities, aiming to provide a broader understanding of the neural mechanisms underlying facial emotion processing in an at-risk population. I contributed novel evidence regarding structural indicators of facial expression recognition abilities across children with varying levels of difficulties (Chapter 5), introducing new avenues for research to comprehend the structural foundations of emotion processing, regardless of diagnostic criteria. I also found differences of brain activation synchronisation linked to emotion processing between children with different levels of facial expression recognition abilities (Chapter 6). In addition, the focus on the level of facial expression recognition abilities rather than categorical diagnostic distinctions highlights the importance of considering individual differences in emotion processing abilities when investigating neural mechanisms. In sum, by examining both the structural and

functional aspects of emotion processing, this thesis looked into the neural mechanisms underlying emotion processing with varying levels of emotional, cognitive, and/or behavioural difficulties.

More directly, the findings in this thesis point to overlapping structure and function relating to facial expression recognition abilities. Specifically, the structural network of gray matter volume covariance, identified in Chapter 5, included the inferior parietal lobe, which was associated with low facial expression recognition abilities. Building upon this, Chapter 6 revealed that children with low facial expression recognition abilities exhibited heightened brain activation synchrony in the inferior parietal lobe. This suggests a potential shared marker for diminished facial expression recognition abilities across both structural and functional investigations. Moreover, this shared marker is present within an at-risk sample, spanning children with emotional, cognitive and behavioural difficulties, as well as a community sample with no known difficulties, suggesting that the inferior parietal lobe's link to facial expression recognition abilities transcends diagnostic boundaries.

The inferior parietal lobe is traditionally associated with motor functions and has emerged as a crucial node in social cognition, including perspective-taking and self-perception (Igelström & Graziano 2017). Recent research by Numssen, Bzdok, & Hartwigsen (2021) further illustrated its functional specialisation across various cognitive domains, e.g., attention, semantics, and perspective taking. Decety & Sommerville (2003) proposed a distributed neural network involving the inferior parietal lobe for self-other discrimination, a finding supported by aTranscranial Magnetic Stimulation (TMS) study. This study showed that self-other discrimination is disrupted when repetitive TMS is applied to this region (Uddin et al. 2006). Moreover, J. Wang et al. (2016) identified subregions within the right inferior parietal lobe, involved in interoception, execution, attention, action inhibition, social cognition, and spatial cognition using both structural and functional MRI.

The findings in Chapters 5 and 6 align well with this body of literature, emphasising the multifunctional role of the inferior parietal lobe in both motor functions and social cognitive

processes. The functional imaging study in Chapter 6, which analysed brain activation synchrony during emotional movie watching, suggests involvement of this region during movie watching, due to the engagement various cognitive domains, including attention and perspective-taking. The findings highlight the significance of inferior parietal lobe as a potential neural marker for emotion processing in an at-risk sample.

7.4 Methodological Considerations

The primary methodological strength of this thesis lies in its emphasis on a transdiagnostic approach and data-driven methodologies. By employing a transdiagnostic approach, I effectively captured the nuanced spectrum of emotion processing across children with varying levels of facial expression recognition abilities. This approach transcends traditional diagnostic categories, providing insights into the complexities of emotion perception across diverse, sub-clinical populations. Furthermore, the utilisation of data-driven approaches in neuroimaging studies was instrumental in exploring the neural profiles of these children. Rather than solely focusing on individual, specific brain regions, this methodology considers the brain as a complex, interconnected system. By analysing data in a holistic manner, the research provides insight into the structural and functional networks underlying emotion processing abilities. Together, these methodological strengths enhanced the depth and breadth of the study's findings, contributing significantly to our understanding of emotion processing in children.

7.4.1 Transdiagnostic Approach

The transdiagnostic approach aims to comprehend the mechanisms underpinning behavioural characteristics shared across individuals with varying abilities, which in turn facilitates a deeper understanding of underlying mechanisms and the development of more tailored interventions (Fusar-Poli et al. 2019; Insel et al. 2010; Stanton et al. 2020). In alignment with the RDoC framework, I employed a transdiagnostic approach throughout my thesis,

acknowledging the diverse range of facial expression recognition abilities among children, moving beyond traditional group comparisons. This approach, anchored in the Systems for Social Processes domain of the RDoC, demonstrated that at-risk children exhibit similar responses to body context influences on facial expressions and share underlying mechanisms with their neurotypical peers. These parallel mechanisms highlight the fundamental aspects of emotional perception processes may be shared across different developmental populations, despite their known difficulties in facial expression recognition, offering novel insights into fundamental principles of emotion processing. Consequently, this approach has broadened our understanding of facial expression recognition beyond traditional diagnostic categories.

In the realm of neuroimaging studies, the integration of children with emotional, cognitive, and/or behavioural difficulties, and a community sample of children within one analysis, enabled the detection of common emotion processing networks, irrespective of children's wider behavioural profiles. In the structural MRI study, we uncovered a common underlying structural network of gray matter covariance associated with facial expression recognition abilities, underscoring the significance of such RDoC-based, transdiagnostic dimensional approaches in understanding shared networks supporting facial expression recognition across diverse behavioural profiles. Similarly, the functional MRI study revealed synchronized brain activation patterns across a similar sample while watching an emotional film clip. Furthermore, differential brain activation synchrony patterns were identified for different facial expression recognition abilities, irrespective of children's wider behavioural profile. By detecting shared structural and functional networks across children with differing levels of facial expression recognition abilities (Y. Zhang et al. 2019), this research lays the groundwork for developing objective biomarkers for emotion processing.

While the transdiagnostic approach holds promise in offering a comprehensive framework for understanding behavioural characteristics, it's crucial to acknowledge its potential drawbacks. One significant concern is the risk of oversimplification inherent in attempting to generalise across diverse profiles. Furthermore, the recruitment of participants for transdiagnostic

studies may be challenging due to the wide-ranging, heterogeneous nature of the sample population. Individuals with comorbid mental health conditions or complex behavioural profiles may be underrepresented, leading to potential biases in study samples (Murray et al. 2019; Sauer-Zavala et al. 2017). Testing children with diverse profiles presents various challenges, including issues related to attention and hyperactivity. For instance, I observed that many children often required frequent reminders about task instructions, and more breaks and reassurance during MRI sessions. However, it is important to note that these challenges varied among children recruited from NDAU, with only some presenting challenges within the testing environment, highlighting the heterogenous nature of this population. Moreover, the inherent heterogeneity underscores the critical need for large sample sizes in behavioural and neuroimaging studies adopting such an approach. Particularly for the studies presented in Chapters 5 & 6, larger samples would have enhanced the reliability and generalisability of findings, providing a clearer understanding of neural mechanisms underlying emotion processing in diverse developmental contexts. Finally, the transdiagnostic approach adopted in this thesis included non-clinical or sub-clinical populations. It would be important to extend this approach to include children with diagnosed conditions, as well as sub- and non-clinical populations, to ensure the findings generalise across diagnostic boundaries into clinical populations.

In summary, while the RDoC holds promise, addressing these challenges through careful recruitment strategies, and larger sample sizes, and broader sampling across the spectrum is important for advancing research in understanding the biomarkers for emotion processing. As future research should continue to refine our understanding of emotion processing, the application of transdiagnostic approaches offer has the potential to offer greater insight into shared mechanisms underpinning emotion processing.

7.4.2 Data-driven Approaches in Neuroimaging

The utilisation of MRI to detect biomarkers associated with specific abilities and diagnoses has undergone significant advancement over the past few decades. Many studies in this field have traditionally relied on prior expert knowledge to guide their focus on specific biomarkers, such as the amygdala in emotion processing (Jiang et al. 2023; Miola et al. 2023; Wiggins et al. 2015), and the fusiform gyrus in face perception (Miola et al. 2023; Hung et al. 2020; McCarthy et al. 1997). However, while this approach has been valuable, its dependence on existing knowledge may inadvertently limit the exploration of biomarkers to expected regions or patterns within the brain. This reliance on predetermined hypotheses, particularly in the study of complex phenomena like emotion processing, can potentially overlook subtle yet crucial nuances. Consequently, there is a growing recognition of the need for more data-driven methodologies that have the capacity to uncover novel biomarkers or patterns of brain activity that might not have been previously considered. By adopting a data-driven approach, researchers have the opportunity to explore brain data in a more unbiased manner, allowing for the discovery of unexpected regions or associations that traditional hypothesis-driven methods might miss.

Data-driven methods hold significant promise in advancing our understanding of neurobiological processes and their link to specific abilities and diagnoses. By leveraging advanced computational techniques and machine learning algorithms, these approaches can uncover previously unrecognised patterns or relationships within brain data. Studies utilising data-driven methodologies have already demonstrated their ability to identify novel biomarkers and elucidate complex neural mechanisms underlying various cognitive functions and mental health conditions (Casanova et al. 2022; Calhoun 2018).

In the current thesis, I applied source-based morphometry on structural data, employing independent component analysis. Independent component analysis provides a data-driven approach, allowing for a comprehensive examination of the entire brain in complex conditions such as schizophrenia (Caprihan et al. 2011; Assche et al. 2023), and autism (Grecucci et al.

2016; Pappaianni et al. 2018). Within source-based morphometry, independent component analysis generates maximally spatially independent component maps, specifically gray matter volume covariation maps in this thesis. These maps capture the contribution of each subject, revealing naturally grouped brain regions without predefined expectations (Calhoun 2018; L. Xu et al. 2009). As a result, I was able to show how this approach reveals the structural network of gray matter volume covariance associated with facial expression recognition abilities across diverse children using this data-driven approach. Furthermore, I highlighted that source-based morphometry provides insights, not discernible through other approaches like voxel-based morphometry, thereby emphasising the role of previously overlooked regions. Overall, source-based morphometry represents a robust data-driven approach that offers an objective framework for addressing uncertainties or absence of clear hypotheses, making it a promising avenue for uncovering the underlying mechanisms of emotion processing across diverse populations and large datasets in research and analysis.

Similar to structural studies, functional studies have often relied on hypothesis-driven approaches, and artificial, static stimuli. However, these methods may fall short in fully capturing real-life experiences, thereby limiting our understanding of how human brain functions in response to dynamic social stimuli (Adolphs et al. 2016; P. A. Chen et al. 2020; Nastase et al. 2019). The integration of naturalistic stimuli in functional studies has transformed our ability to recreate real-world conditions (Saarimäki 2021). The utilisation of complex, dynamic, and naturalistic stimuli, which encompass facial expressions, contextual cues, social interactions, and language, allow for the observation of brain network dynamics in response to more realistic social conditions (Adolphs et al. 2016; Nastase et al. 2019). One such data-driven approach utilising naturalistic stimuli is intersubject correlation analysis, as applied in Chapter 6. This methodology offers valuable insights into brain activation synchrony, revealing how individuals respond similarly to naturalistic stimuli. By examining brain activation synchrony in response to the emotional stimuli, I was able to observe both similarities and differences in synchronization among children exhibiting differing levels of

facial expression recognition abilities.

Data-driven approaches encounter several limitations, notably stemming from the absence of a prior hypothesis or theory, which complicates interpretation of the results and assigning meaning to extracted components or dimensions. While some findings extracted from data-driven approaches may intuitively align with the existing literature, others may not, leading to issues in separating meaningful data from artefacts, like participant movement while in the scanner. Finally, determining the validity of independent components identified relies on the researcher's interpretation, underscoring a subjective element in the analysis of data-driven methodologies (Calhoun 2018).

7.5 Conclusion

In summary, this thesis has shown that children with diverse behavioural profiles utilise similar mechanisms to integrate facial and body expressions. The proficiency in recognising isolated facial expressions determines their susceptibility to being influenced by incongruent body expressions. This finding persists despite many children exhibiting substantial difficulties in facial expression recognition performance but not in body expression recognition. Additionally, I revealed a structural network of grey matter volume change related to children's facial expression recognition ability, involving frontal and temporal regions. This finding emphasises the importance of adopting a transdiagnostic approach, which allows exploring structural markers of facial expression processing in the brain irrespective of children's broader emotional, cognitive, and/or behavioural difficulties. Additionally, both similarities and differences in brain activation synchrony while watching an emotional movie clip were identified between children with low and high facial expression recognition abilities in regions like inferior parietal lobe, frontal pole, medial frontal gyrus, and ventromedial prefrontal cortex. This indicates that children with different levels of facial expression recognition abilities exhibit both similar and distinct brain activation synchrony in response to an emotional movie. Importantly,

both structural and functional imaging findings were regardless of children's wider profile of difficulties, capturing neural markers of emotion processing across a spectrum. These findings underscore the value of a transdiagnostic approach in understanding the neural mechanisms underlying emotion processing in at-risk populations.

Appendices

Appendix A

Slope	**ROI**	**cluster-level FWE**	**k**	**uncor p-value**	**peak-level FWE**	**t**	**Z**	**MNI X Y Z**
Positive								
	OFC R	0.171	4	0.851	0.144	3.5	3.22	58 36 -4
	Middle Temporal Gyrus L	0.14	30	0.539	0.025	4.39	3.89	-52 -45 -10
Negative								
	Middle Cingulate Gyrus R	0.114	5	0.829	0.084	3.57	3.28	10 -21 33
	Middle Temporal Gyrus R	0.189	6	0.81	0.195	3.43	3.16	56 -15 -10
	Superior Temporal Gyrus R	0.095	31	0.532	0.118	3.53	3.24	56 -15 -8

Table 1: The full list of clusters showing positive and negative correlation between GMV and negative FER at $p<0.001$ uncorrected at the whole-brain level. *uncor: uncorrected

Appendix B

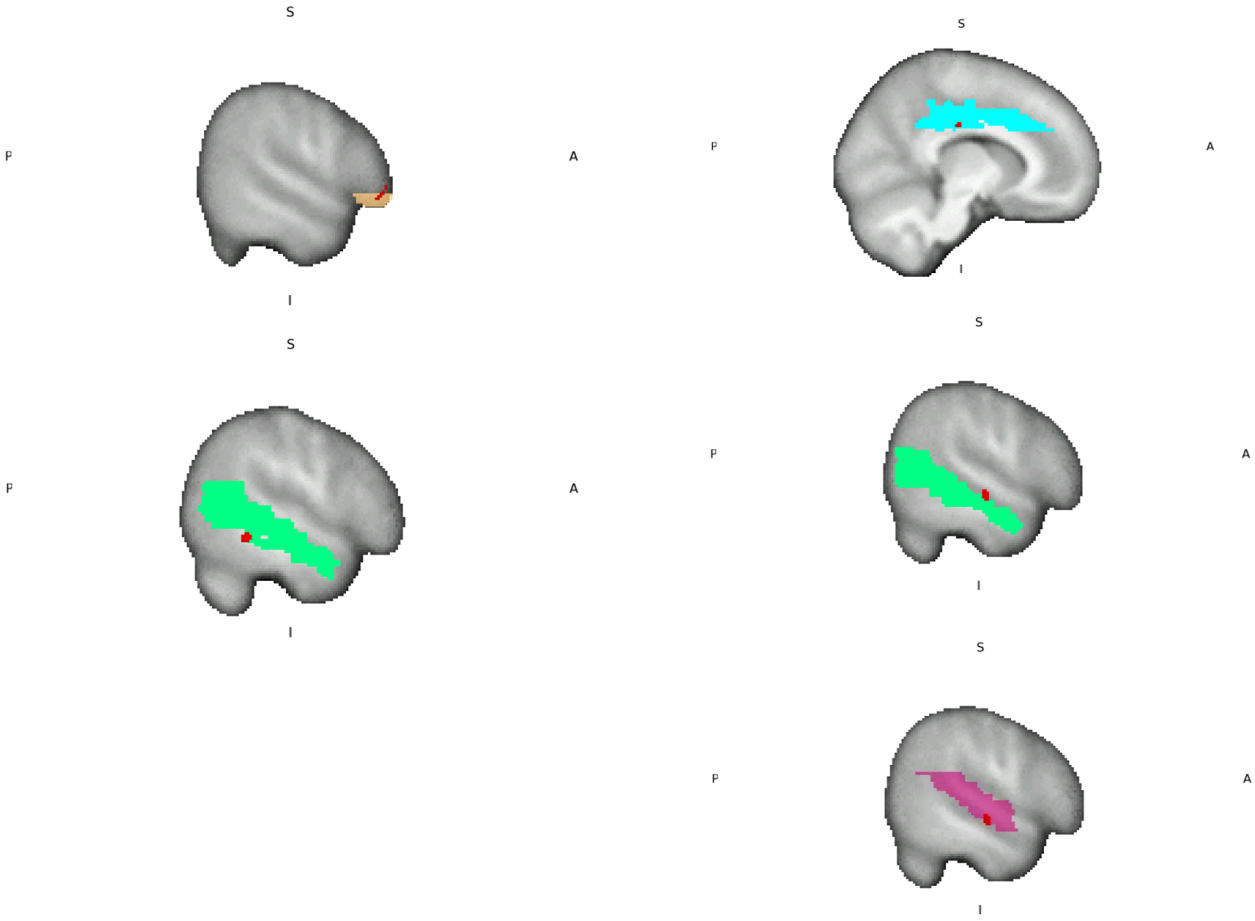

Figure 1: The ROI clusters shown on the brain. Red represents the identified cluster at p<0.001 uncorrected at whole-brain level. Right OFC ROI mask (Copper), Left MTG ROI mask (Light Green), Right Middle Cingulate Gyrus ROI mask (Light Blue), and Right STG ROI mask (Pink) (a) OFC R. (b) MTG L. (c) Middle Cingulate Gyrus R. (d) MTG R. (e) STG R.

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