Zur Plastizität von sozio-emotionalen Kompetenzen auf Verhaltens- und Gehirnebene:

Eine EEG-begleitete Trainingsstudie bei Vorschulkindern mittels des computergestützten Trainingsprogramms Zirkus Empathico

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Und an alle, die mich noch einmal fragen:
- „Na, wie weit bist du mit der Promotion?“
Kann ich jetzt antworten:
- „Fertig.“

Abstract

Preschool years (3-6 years) represent a crucial time for the development of socio-emotional competence, as children's interactions with others become more complex and frequent, thereby presenting numerous opportunities for social learning. Similarly, psychological disorders may manifest for the first time during this period of development, where socio-emotional competence may serve as an essential resilience factor. Promoting functional socio-emotional competence within this age range is thus crucial for preventing the emergence of psychiatric disorders and fostering school readiness.

Classroom-based trainings have already demonstrated the potential of socio-emotional competence programs for preschoolers. Recently, focus has been placed on digital trainings that offer opportunities for training outside of the classroom. However, to date, there are few studies examining the impact of digital trainings on preschoolers' socio-emotional development. Similarly, behavioral research provides extensive information on the typical development of preschoolers, whereas less is known about how the brain realizes these functions at this age. Moreover, neurobiological systems are infrequently considered in the evaluation of training efficacy. Consequently, the purpose of this dissertation was to elucidate fundamental and complex aspects of preschoolers' socio-emotional competence by assessing their maturity and trainability, particularly with digital trainings, using behavioral and neuronal measures.

In Studies 1 and 2, event-related potentials (ERPs) and the fast period visual stimulation (FPVS) approach were used to quantify the neuronal mechanism of emotion recognition, which is fundamental socio-emotional competence that lays the foundation for more complex aspects of socio-emotional competence. Both studies indicated that the fundamental mechanisms of emotion recognition are present in this age range. In addition, preschoolers differentiated emotions with a processing advantage for happy faces over angry or neutral ones.

Study 3 examined the trainability of socio-emotional competence using the digital training Zirkus Empathico. The effects were evaluated using parental questionnaires, child assessments, and ERP markers validated in Study 1. The training was administered in children's homes for six weeks. The training group was paired with an active control group that trained with an application for English language acquisition. Participants in the Zirkus Empathico group demonstrated increases in both fundamental (emotion recognition) and complex (empathy, prosocial behavior) socio-emotional competence compared to controls. Moreover, only the Zirkus Empathico group demonstrated ERP modulations by facial expressions at higher-order neuronal processing stages, indicating a processing advantage of happy faces.

In conclusion, the utility of neuronal markers for evaluating the mechanisms underlying preschoolers' emotion recognition was demonstrated, allowing for discussion on how to use ERP and FPVS markers in the future. Moreover, the promising evidence for the efficacy of a digital socio-emotional competence training permits for additional discussions regarding sustainability of effects and its social significance. Lastly, implications for future research include considerations for capturing (socio-emotional) development more accurately and comprehensively across the preschool period.

Zusammenfassung

Die Vorschulzeit (Altersspanne 3-6 Jahre) ist entscheidend für die Entwicklung sozio-emotionaler Kompetenzen, da Interaktionen von Kindern mit anderen Menschen immer komplexer und häufiger werden und sich somit zahlreiche Gelegenheiten für soziales Lernen ergeben. Gleichzeitig können sich in dieser Entwicklungsphase erstmals psychische Störungen manifestieren, wobei funktionale sozio-emotionale Kompetenz einen wesentlichen Resilienzfaktor darstellt. Die Förderung funktionaler sozio-emotionaler Kompetenzen in dieser Altersgruppe ist daher von entscheidender Bedeutung, um der Entstehung psychischer Störungen vorzubeugen und die Schulfähigkeit zu fördern.

Das Potenzial von Programmen zur Förderung der sozio-emotionalen Kompetenz von Vorschulkindern wurde bereits anhand von Gruppentrainings in Kindergärten nachgewiesen. Neuerdings stehen auch digitale Programme im Fokus, die Möglichkeiten für ein Training außerhalb des Kindergartens bieten. Bislang gibt es jedoch nur wenige Studien, die die Auswirkungen digitaler Trainings auf die sozio-emotionale Entwicklung von Vorschulkindern untersuchen. Ebenso liefert die Forschung umfangreiche Informationen über typisches sozio-emotionales Verhalten bei Vorschulkindern, während weniger darüber bekannt ist, wie das Gehirn diese Funktionen in diesem Alter umsetzt. Außerdem werden neurobiologische Systeme bei der Bewertung der Wirksamkeit von Trainings nur selten berücksichtigt. Ziel dieser Dissertation war es daher, grundlegende und komplexe Aspekte der sozio-emotionalen Kompetenz von Vorschulkindern zu untersuchen, indem ihre Reife und Trainierbarkeit mit Verhaltens- und neuronalen Maßen erfasst wurden.

In den Studien 1 und 2 wurden ereigniskorrelierte Potenziale (EKPs) und die Fast Periodic Visual Stimulation (FPVS) Methode eingesetzt, um neuronale Mechanismen der Emotionserkennung zu quantifizieren. Emotionserkennung stellt eine grundlegende Kompetenz dar, welche die Basis für komplexere Aspekte der sozio-emotionalen Kompetenz bildet. Beide Studien ergaben das Vorhandensein grundlegender Mechanismen der Emotionserkennung in dieser Altersgruppe. Darüber hinaus zeigten Vorschulkinder einen Verarbeitungsvorteil von fröhlichen gegenüber wütenden oder neutralen Gesichtern.

Studie 3 untersuchte die Trainierbarkeit sozio-emotionaler Kompetenz anhand des digitalen Trainings *Zirkus Empathico*. Die Effekte wurden mithilfe von Elternfragebögen, Einschätzungen der Kinder und EKP-Markern, die in Studie 1 validiert wurden, bewertet. Die Kinder trainierten über einen Zeitraum von sechs Wochen. Die Trainingsgruppe wurde mit einer aktiven Kontrollgruppe verglichen, die den englischen Spracherwerb trainierte. Die Zirkus-Empathico-Gruppe zeigte im Vergleich zur Kontrollgruppe einen Anstieg sowohl der grundlegenden (Emotionserkennung) als auch der komplexen (Empathie, prosoziales Verhalten) sozio-emotionalen Kompetenzen. Darüber hinaus ergab sich für die Zirkus-Empathico-Gruppe auf der neuronalen Ebene einen Verarbeitungsvorteil für fröhliche Gesichter.

Zusammenfassend zeigt sich ein erheblicher Nutzen neuronaler Marker für das Verständnis von Mechanismen, welchen der Emotionserkennung von Vorschulkindern zugrunde liegen. Dies ermöglicht eine weiterführende Diskussion über den Einsatz von EKP- und FPVS-Markern in der Zukunft. Die vielversprechende Evidenz für die Wirksamkeit eines digitalen sozio-emotionalen

Kompetenztrainings ermöglicht darüber hinaus weitere Überlegungen zur Nachhaltigkeit der Effekte sowie der gesellschaftlichen Bedeutung. Implikationen für die zukünftige Forschung umfassen genauere und umfassendere Erhebungsmöglichkeiten der (sozio-emotionalen) Entwicklung bei Vorschulkindern.

Contents

List of Original Publications

This dissertation is based on research experiments that have been published or are under revision in peer-reviewed journals.

Study 1: Naumann, S., Bayer, M., & Dziobek, I. (2022). Preschoolers' Sensitivity to Negative and Positive Emotional Facial Expressions: An ERP Study. *Frontiers in Psychology,* 13, 828066. https://doi.org/10.3389/fpsyg.2022.828066.

Study 2: Naumann, S., Bayer, M., & Dziobek, I. (2022). Enhanced neural sensitivity to brief changes of happy over angry facial expression in preschoolers: A fast periodic visual stimulation study. https://doi.org/10.31234/osf.io/ucvkj [under review, currently available as preprint].

Study 3: Naumann, S., Bayer, M., Kirst, S., van der Meer, E. & Dziobek, I. (2023). A randomized controlled trial on the digital socio-emotional competence training Zirkus Empathico for preschoolers. *npj Science of Learning.* 8, 20. https://doi.org/10.1038/s41539-023-00169-8

1

General Introduction

Do you ever look at someone and wonder:

'What is going on inside their head?'

Opening line from the Disney movie "Inside Out" (2015)

1. General Introduction

Social interactions are fundamental to our existence. When establishing contact with others, we must consider not only our own intentions, but also what our counterpart is currently thinking or experiencing, which can be challenging. Socio-emotional competence incorporates our comprehension, expression, and regulation of our own and others' emotions, thoughts, and behaviors, as well as our responses (Schoon, 2021). This competence is primarily shaped by socialization and thus develops gradually over the course of a lifetime (Denham et al., 2009; Schoon, 2021). Unquestionably, the preschool years (3-6 years)[1] mark the beginning of more complex behaviors and thoughts associated with socio-emotional competence (Beauchamp & Anderson, 2010; Denham et al., 2009). As preschoolers interact more with their environment and, consequently, engage in numerous social interactions (Denham et al., 2009), rapid maturational and experiential changes occur rapidly in this phase, paving the way for quantitative and qualitative leaps in social-emotional competence development (Salerni & Caprin, 2022). Beyond changes in observable behaviors, the emergence of sophisticated socio-emotional competence has also been linked to a complex "social" brain network, which is still maturing during preschool and reaches gradual functional specialization throughout childhood and adolescence (Beauchamp & Anderson, 2010).

Normative socio-emotional competence plays an essential part in school readiness (Slot et al., 2020) and predicts subsequent academic success (Denham, 2018). In contrast, disruptions in the development of socio-emotional competence can result in psychological distress and increase the likelihood of engaging in problematic behavior (Beauchamp & Anderson, 2010; Beelman, 2019). Therefore, it is not surprising that the preschool years are the time when psychological problems manifest and become apparent to others for the first time (Beelman, 2019; Steinsbekk et al., 2022; Tobarra-Sanchez et al., 2022). Functional socio-emotional competence on the other hand can constitute an important resilience factor against the manifestation of psychological problems (Alwaely et al., 2021; Colomeischi et al., 2022; Romppanen et al., 2021), predicting valued life outcomes such as well-being and life satisfaction (Schoon, 2021).

In light of (1) the increasing exposure to social interactions and (2) the high risk of early manifestation of psychological disorders due to possible disruptions in the development of social

[1] Within this dissertation, I adhere to the definition of Stangl (2022) who defines preschool age as a period starting from the fourth year of life (equals the third birthday) until the German primary school enrollment (typically after sixth birthday).

competence (Fryers & Brugha, 2013), the promotion of functional socio-emotional competence during preschool represents an essential step to facilitate continued development throughout adolescence and beyond (Beauchamp & Anderson, 2010). In recent decades, significant progress on the evaluation of social-emotional competence training programs targeting preschool classrooms has been made (Beelman, 2019). However, incidents such as the COVID-19 pandemic have made it obvious how crucial it is to promote training beyond the kindergarten setting (Egan et al., 2021; Murano et al., 2020). Due to children's high approval of digital media, design factors to increase motivation (such as the incorporation of videos or reward systems), and individualization opportunities, digital trainings appear to be of particular interest in this context (Herodotou, 2018; Hollis et al., 2020; Whyte et al., 2015). To date, however, there are only few studies examining the potential of individual trainings, particularly digital approaches, for the development of preschoolers' socio-emotional competence (Wu & Kim, 2019).

In addition, neurobiological systems in general, and the evaluation of training efficacy, in particular, would be helpful to understand preschoolers' socio-emotional development in fuller complexity (Cicchetti & Gunnar, 2008). Measuring the socio-emotional competence of young children poses challenges (e.g., natural limitation on cognitive and attentional resources). Brain measurements may thus serve as correlates for aspects of socio-emotional competence (e.g., emotion perception) that are difficult to collect otherwise. In addition, child development is not linear (Beauchamp & Anderson, 2010), implying that what we observe as a new behavior (e.g., a child is able to assume the perspective of another child) is the result of a number of continuously changing processes that are not necessarily visible from the outside (including brain changes such as myelination or changes in synaptic density; Parker & Nelson, 2005). Thus, brain correlates may facilitate the measurement of differences in social stimulus processing that may not yet manifest in behavior (e.g., Leppänen et al., 2007; Parker & Nelson, 2005). The majority of developmental neuroscience research, however, has thus far centered on infancy, late childhood, and early adolescence, while preschool period has received less attention (Bayet & Nelson, 2019; Morales & Fox, 2019). In addition, the majority of preschool research focuses on clinical groups (e.g., autism: Dawson et al., 2004; traumatic brain injury: D'Hondt et al., 2017), whereas little is known about how the brain realizes facets of socio-emotional competence in preschoolers (Morales & Fox, 2019).

Consequently, the overall purpose of this dissertation is twofold: On the one hand, neuronal mechanisms underlying the socio-emotional competence of typically developing preschoolers will be investigated in order to fathom their normative development. On the other hand, the dissertation will investigate whether socio-emotional competence can be

trained and how changes in behavior and the brain manifest in this age group.

In the following chapters, I introduce emotion recognition, empathy, and prosocial behavior as three components of socio-emotional competence that become increasingly complex beginning in early childhood. I use findings from behavioral and brain studies to illustrate previous insights on the typical socio-emotional development of preschoolers. Further, I introduce current behavioral and neuronal measures of socio-emotional competence and provide an overview of previous efforts to train socio-emotional competence in preschoolers. Here, I specifically focus on more recent efforts to integrate digital socio-emotional competence trainings with neuronal correlates to measure training efficacy. On the basis of this theoretical overview, I present three studies conducted for this dissertation that sought to elucidate socio-emotional competence in typically developing preschoolers by assessing their maturity, as an indicator of normative development, and trainability with behavioral and brain measures. In the final chapter, I interpret and summarize the results of my research. I discuss the implications of this dissertation for the normative socio-emotional development of preschoolers and the possibility of promoting socio-emotional competence, as well as the impact and challenges of digital competence trainings.

1.1 Preschoolers' Socio-Emotional Competence Development

This chapter is devoted to delineating the relevant concepts for my work. Firstly, I examine the overall construct of socio-emotional competence. Facets of this construct pertinent to this dissertation, namely emotion recognition, empathy, and prosocial behavior, are then presented in the context of their development through early childhood.

1.1.1 Definition of Socio-Emotional Competence and Interrelationships between Constructs

Although many studies are dedicated to the topic of socio-emotional competence, there is neither consensus about the definition nor the number of core components (Abrahams et al., 2019; Schoon, 2021). In the context of child development, socio-emotional competence is mostly assumed to be a conglomerate of social and emotional skills that contribute to a child's ability to both adapt to social situations and appropriately assert own needs and interests over others (Holodynski & Rüth, 2021). The construct is typically constrained by a strong emphasis on social competence, which reflects the effectiveness of children in their social interactions with others (e.g., making and sustaining social connections or demonstrating cooperative skills; Halle & Darling-Churchill, 2016), and which is typically operationalized with concrete social behavior (e.g., prosocial behavior; Beelman, 2019; L. Luo et al., 2022). However, an important extension constitutes the integration of emotional competence (e.g., as implemented in the Affective Social Competence model; Halberstadt et al., 2001), which is defined as the ability to understand own and others' emotions, react to others' emotions, regulate one's own emotions, and understand the consequences of one's emotional expressiveness (Halle & Darling-Churchill, 2016). Though often neglected in research (see L. Luo et al., 2022 for meta-analysis), the assessment of emotional competence is of particular importance in preschoolers due to dynamic developmental changes (e.g., learning to understand expressions of basic emotions; Denham et al., 2009) that correspond significantly with the quality of social competence within this age range (Beelman, 2019). Thus, this dissertation examined both preschool-relevant components of social *and* emotional competence. Emotion recognition and empathy were selected as components of emotional competence, whereas prosocial behavior was chosen as a component of social competence.

Emotion recognition is regarded as the foundation for more complex socio-emotional competence components such as empathy and prosocial behavior. Different findings substantiate this assumption: Emotion recognition, especially from facial expressions, is a fundamental component of emotion perception (Halberstadt et al., 2001; LoBue et al., 2019). Further, the ability to recognize and comprehend the emotions of others enables children to comprehend feelings and intentions of others in social interactions (Ornaghi et al., 2019). When children can recognize signs of distress in others (such as an angry or sad expression), they are able to intervene empathically or prosocially in a variety of situations (Grueneisen & Warneken, 2022). It is therefore not surprising that empathic concern and prosocial behavior have a robust positive relationship with accurate emotion recognition (Farina & Belacchi, 2022; Israelashvili et al., 2020; Trentacosta & Fine, 2010).

Moreover, empathy is one of the most extensively researched factors influencing prosocial behavior (Yin & Wang, 2022). While some research has suggested that empathy is positively related to prosocial behavior (see Yin & Wang, 2022 for meta-analysis) and constitutes the foundation for its development (Song, 2022), other studies have shown that empathy is not always accompanied by a prosocial response (Cuff et al., 2016). The preschool years reveal clear developmental leaps in emotion recognition, empathy and, prososcial behavior, which are described below (Camras & Halberstadt, 2017; Denham, 2018; Grueneisen & Warneken, 2022).

1.1.2 Emotion Recognition from Facial Expressions: Establishing the Foundation

The recognition of emotions, particularly from facial expressions, constitutes the most rudimentary stage of processing social cues and is considered the primary means of emotional communication for young children (Beauchamp & Anderson, 2010). Emotion recognition includes the awareness that an emotion has been expressed (typically through relevant facial cues, e.g., raised eyebrow, smile), and the labeling of (non-)prototypical expressions (Castro et al., 2016). To date, there is no unified or systematically-tested theory on children's emotional development (Buss et al., 2019). The *differential emotion theory* (Izard, 1971) assumes that humans are equipped with a basic universal set of emotions. According to this theory, emotions can be classified into discrete categories, distinguishable by for example certain facial features (e.g., a smile indicates that an individual is happy; Izard, 2007). In terms of development, the differential emotion theory postulates that the fundamental set of emotions interacts with cognitive systems to form emotion schemas, resulting in more complex emotions. Hence, basic emotions (e.g., happiness) mature earlier than other more complex emotions (e.g., guilt) as they need more cognitive effort.

Indeed, most research on children's emotion recognition development stems from the examination of unambiguous, discrete emotions expressed in facial expressions (Trentacosta & Fine, 2010). The findings partially support the differential emotion theory: Infants, for instance, appear to perceive facial expressions as relatively undifferentiated states, with features displaying either a positive or negative expression (Beauchamp & Anderson, 2010; Buss et al., 2019). By preschool age, children are able to detect and express basic emotions (e.g., happiness, anger, fear; Denham, 2018). While happy facial expressions are recognized with almost adult-like precision, children are less accurate with negative facial expressions (see Bayet & Nelson, 2019 for review). These findings suggest a progressive differentiation from broad to more fine-grained emotion distinctions (Camras & Halberstadt, 2017). Younger children seem to use broad valence-based categories (e.g., positive vs. negative) and only later develop the ability to accurately use more specific discrete category labels for emotional expressions (LoBue et al., 2019).

1.1.3 Multidimensional Aspects of Empathy Development

There have been numerous attempts to find a unitary definition for the construct of empathy (Cuff et al., 2016; Hein & Singer, 2008). Most commonly, empathy refers to a multidimensional concept, which comprises separate but interrelated cognitive and affective facets (Cuff et al., 2016; Dziobek et al., 2008). *Cognitive empathy* refers to the capacity to take the perspective of others and infer their mental states (Blair, 2005). In contrast, *affective empathy* focuses on the emotional experience evoked by an emotional stimulus (Cuff et al., 2016). Collectively, empathy is the emotional competence to feel *as* another individual, which emphasizes understanding and sharing another's emotions (Hein & Singer, 2008). *Empathic concern,* which refers to empathic feelings for the other, is subsumed by some under affective empathy (Knafo et al., 2008), whereas others have defined them as separate constructs (Decety et al., 2018).

According to Hoffman's (2000) stage theory of empathy development, neonates are born with the capacity for rudimentary empathic distress, which is the involuntary experience of another individual's agonizing emotional state (Hoffman, 2000). Studies demonstrated that newborns wept more contagiously when exposed to the sound recording of another infant's cry as opposed to their own (Sagi & Hoffman, 1976). Referring to an alternative and more recent perspective, Davidov et al. (2013) found that the empathic response repertoire of neonates during their first year was not limited to empathic distress. As a very early form of cognitive empathy, it also included empathy for another person and the earliest endeavors to understand others' distress (Davidov et al., 2013; Liddle et al., 2015). During the first three years of life, affective empathy, in particular, appears to remain stable or to increase only minimally (Decety et al., 2018). In turn, preschool years seem to mark the emergence of higher cognitive empathy (Denham, 2018; Liddle et al., 2015). By this age, children have developed the cognitive flexibility to consider the perspectives of others and to effectively ruminate on situations that have an impact on them (Li et al., 2019).

1.1.4 Maturing from Sympathy-Based to Strategic Prosocial Behavior

Prosocial behavior consists of positive interactions with other people, such as assisting, sharing, cooperating, and comforting, which have a positive impact on social relationships (Beauchamp & Anderson, 2010; Salerni & Caprin, 2022; Yin & Wang, 2022). Children's prosociality develops from being mostly sympathy-based to becoming more behaviorally varied, more selective, and strategic as well as more motivationally and cognitively complex (Grueneisen & Warneken, 2022; Kenward & Dahl, 2011). Sympathy-based prosocial behavior is solely focused on the facilitation of the recipient's goal and needs, whereas more strategic prosocial actions may also include a self-serving purpose (e.g., 'If I help you now, maybe you will help me another time.'; Grueneisen & Warneken, 2022). The early emergence of a wide range of spontaneous positive behaviors is well documented by the end of the first year of life (Salerni & Caprin, 2022): Children notice others' negative states such as unmet needs or negative emotional experiences, and are intrinsically motivated to alleviate these negative states (Grueneisen & Warneken, 2022). Between 14 and 18 months, children start to help others reach practical goals, for example, by fetching out-of-reach objects or by removing a barrier (Grueneisen & Warneken, 2022; Warneken & Tomasello, 2013). Engaging in strategic prosociality first emerges around age 4 to 5 and becomes more sophisticated in the following years (Salerni & Caprin, 2022). For example, toddlers share as many toys with prosocial individuals as with individuals from whom they had not experienced prosocial actions (Warneken & Tomasello, 2013). In contrast, preschoolers are more prosocial toward individuals who had helped them before (Kenward & Dahl, 2011).

1.2 Assessing Emotion Recognition, Empathy and Prosocial Behavior

Based on the variety of definitions of socio-emotional competence, there is a spectrum of approaches to measuring them (Abrahams et al., 2019; Halle & Darling-Churchill, 2016; Schoon, 2021). The majority of the evidence pertaining to the development of young children has been derived from behavioral research. It thus remains challenging to infer how the brain implements socio-emotional processing within this age range due to the paucity of neuroscientific findings (Morales & Fox, 2019). The integration of neuronal insights provides a crucial component for understanding socio-emotional processing that might not yet be apparent in behavior (Leppänen et al., 2007), and thus aids in comprehending the complexity of socio-emotional development. Consequently, the following overview describes methods for measuring emotion recognition, empathy, and prosocial behavior in preschoolers that incorporate behavioral *and* brain correlates. The focus is on neuronal correlates for emotion processing from facial expressions, as these serve as the basis for other, more complex components of socio-emotional competence.

1.2.1 Evaluating Preschoolers' Behavior with Assessment, Observation, and Parental Report

In order to track and evaluate developmental processes, it is considered a gold standard to collect data from multiple sources (Dirks et al., 2012; Mondi et al., 2021; Sessa et al., 2001). Most developmental studies therefore employ a set of teacher or parental reports or child observations as well as performance-based assessments (e.g., development-appropriate emotion matching task, Abrahams et al., 2019). Firstly, there is an overall shortage of measures for very young children with well-established psychometric properties of socio-emotional competence (L. Luo et al., 2022). Assessing behavioral components of preschoolers' socio-emotional competence presents a number of obstacles: Children are rudimentarily capable of revealing their cognitive and emotional states (see Halle & Darling-Churchill, 2016 for review). Additionally, it can be difficult to administer tests because young children naturally have limited attentional and cognitive capabilities (e.g., Johnston et al., 2011).

Matching a picture of a facial expression to a feeling's label (e.g., matching a smiling face with the word "happy") is a common component of child assessments of emotion recognition from facial expressions (e.g., Durand et al., 2007; Gao & Maurer, 2010; Johnston et al., 2011). For the evaluation of empathy and prosocial behavior in preschoolers, suitable tasks include situational judgment tasks (Abrahams et al., 2019): Children are provided with a set of hypothetical scenarios, or vignettes, accompanied by several plausible courses of action (e.g., "Maria is afraid of dogs. She goes on a walk and sees a dog. What will Maria do? What can you do to help Maria?"). Answers are then rated according to their appropriateness in that situation (Abrahams et al., 2019). In general, typical performance within these ascribed tasks increases with age, but it heavily depends on the specific task and the employed stimulus material (Bayet & Nelson, 2019).

1.2.2 Unwrapping the Maturing Social Brain Network

As one neuroscientific method for measuring neuronal correlates of socio-emotional competence, functional magnetic resonance imaging (fMRI) is used to analyze the activity of different brain regions and networks with high spatial resolution (Morales & Fox, 2019). Previous studies indicated that, comparable to adults, the recognition of facial expressions in preschoolers engages a widely distributed network of brain areas including visual (e.g., fusiform gyrus), emotional (e.g., limbic structures), as well as other temporal and (sub-)cortical neuronal processing pathways (Fusar-Poli et al., 2009; LoBue et al., 2019). Preschoolers appear to have greater amygdala activation in response to facial expressions than adults, which may indicate heightened sensitivity to emotional features (Hoehl et al., 2010). The increased activation may be due to the ongoing maturation of cognitive control systems, such as prefrontal brain regions, which mature later in both structure and function than subcortical brain regions (MacNamara et al., 2016). A similar pattern can be found for empathy: The amygdala, the posterior insula, and the supplementary motor area were all more active in children than in adults when they were exposed to empathy-eliciting stimuli (Decety & Michalska, 2010). In addition, activation in the anterior insular cortex (AIC) and the anterior cingulate cortex (ACC) which correlated with empathic concern has been already observed in four-year-old children (Michalska et al., 2013). It was hypothesized that affective empathy in particular requires the recruitment of emotional processing regions (Hein & Singer, 2008). In contrast, cognitive empathy seems to be associated with brain areas related to regulatory mechanisms such as cognitive control and response inhibition which still mature until early adulthood (Beauchamp & Anderson, 2010; Hein & Singer, 2008). For example, greater activity in the dorsolateral prefrontal cortex (DLPFC) and inferior frontal gyrus (IFG) to empathy-eliciting stimuli has been detected with increasing age (Decety & Michalska, 2010). Lastly, cognitive control is crucial for prosocial behaviors such as deciding to share or to help others (Steinbeis et al., 2012). Previous research suggested that the maturation of the prefrontal cortical circuitry also supports the development of prosocial behavior during childhood (Steinbeis, 2018), particularly the DLPFC associated with the decision to favor long-term goals (Steinbeis et al., 2012). In addition, overlapping activity of neuronal circuits linked to prosocial behavior and empathic concern such as the AIC has been reported (Hein et al., 2010).

1.2.3 Quantifying the Neuronal Time Course of Preschoolers' Facial Expression Processing

With its excellent temporal resolution, electroencephalography (EEG) allows to investigate the neurophysiological mechanisms underlying socio-emotional processing (Bhavnani et al., 2021; Hoyniak et al., 2019; Morales & Fox, 2019). EEG is an exceptional instrument for detecting the otherwise inaccessible early processing markers of face processing, in contrast to the fMRI method, which lacks temporal dynamics measurements (Schindler & Bublatzky, 2020). The fMRI method is also highly susceptible to participants' movements and requires a high degree of compliance (Morales & Fox, 2019). In contrast, EEG is a non-invasive, readily applicable method that permits the rapid and accurate assessment of millisecond-scale neurocognitive processes in real time, particularly in young children (D'Hondt et al., 2017). Most developmental neuroscience work, however, has focused on late infancy, childhood or early adolescence, which is in strong contrast to the behavioral work, in which there are decades of work on preschool development (see for Bayet & Nelson, 2019; Morales & Fox, 2019 review). In addition, most of the previous EEG research with young children stems from the assessment of clinical groups (e.g., traumatic brain injury, maltreatment, e.g., Curtis & Cicchetti, 2011; D'Hondt et al., 2017), with only a handful of studies examining the maturity in typically developing preschoolers (e.g., Batty & Taylor, 2006; Hoyniak et al., 2019; Vlamings et al., 2010). Therefore, additional research is required to examine the neuronal mechanisms of facial expression processing in order to evaluate the typical preschool development (Bhavnani et al., 2021). EEG measurements of facial expression processing employing both event-related potentials (ERPs) to assess neuronal trajectories and frequency band information elicited by fast period visual stimulation (FPVS) paradigms are of particular interest for this dissertation.

Event-Related Potentials

In EEG experiments with ERP measurements, stimuli of the same type (e.g., happy facial expressions) are usually presented repeatedly. Afterward, averaging the EEG portion which was recorded directly after the presentation of one stimulus type leads to the emergence of ERP components (Luck, 2014; Morales & Fox, 2019). They can be classified according to their polarity (positive vs. negative), appearance in time, and topography (Luck, 2014). One of the most common EEG experiments for facial expression processing employed in developmental samples constitutes the *passive face viewing paradigm* (e.g., Batty & Taylor, 2006; D'Hondt et al., 2017; Hoyniak et al., 2019; Leppänen et al., 2007; Porter et al., 2021; Xie et al., 2019). The paradigm involves the repeated presentation of facial expressions, while the participant passively observes the stimuli. One of the assumptions of the passive face viewing paradigm follows the differential emotion theory (outlined in detail in chapter 1.1.2) claiming that emotions can be perceived as discrete categories and that every emotion has a specific pattern of neuronal activity (Buss et al., 2019). The most prevalent emotions utilized in developmental EEG research are derived from the differential emotion theory's fundamental set of emotions (happiness, anger, fear, surprise, sadness, and disgust; e.g., Izard, 1971, 2007).

In general, findings from passive face viewing paradigms indicate that preschool-aged children exhibit a range of ERP responses similar to those described in the literature on facial expression processing for adults (e.g., Batty & Taylor, 2006). Modulations by facial expressions have been observed in early ERP components (e.g., visible from around 50 to 100 ms after the face was presented) and late ERP components (e.g., visible from around 300 ms), which can also be classified into several stages of facial emotion perception (for review see Schindler & Bublatzky, 2020): The initial sensory processing and automatic detection of facial expressions has been associated with modulations in the P1 component (Ding et al., 2017), which peaks at 100 ms post-stimulus presentation and seems to have generators in primary visual cortex areas (Di Russo et al., 2002). Secondly, modulations in the negative N170 component, which peaks around 170 ms, were linked to the processing of configural information (e.g., detecting facial parts in relation to each other; Schindler & Bublatzky, 2020) as well as the parallel processing of facial identity and expression (Hinojosa et al., 2015). The fusiform gyrus and the superior temporal sulcus (STS) are possible brain regions that contribute to modulations in the N170 (see Rossion & Jacques, 2008 for review). The P1 and N170 as early ERP components were the most commonly reported neuronal responses to face and expressive face stimuli (see Bhavnani et al., 2021 for review). Subsequently, the P3 as a late ERP component is typically visible in a time window beginning between 250 and 500 ms (Brooker et al., 2020) and may have neuronal generators across extensive occipito-parietal regions (Sabatinelli et al., 2013). Modulations have been associated with the integration of emotional information with task-related and semantic information (Schindler & Bublatzky, 2020) as well as motivational saliency (Hajcak & Dennis, 2009).

According to the few existing studies with preschool samples, positive and negative facial expressions led to increases in the amplitudes of these early and late components in preschoolers when compared to neutral facial expressions (Curtis & Cicchetti, 2011; Vlamings et al., 2010). Although EEG does not directly index activity from subcortical brain structures, it is possible that the observed enhancement in activity for facial expressions reflects neuronal circuits that involve the amygdala (Morales & Fox, 2019). Prior research demonstrated that direct amygdala projections to the occipital cortex may facilitate the processing of visually salient stimuli such as facial expressions (Eimer et al., 2003; Vuilleumier & Pourtois, 2007). The increased neuronal sensitivity to expressive as compared to neutral faces may also be linked to ongoing functional brain organization and hemispheric specialization (Batty & Taylor, 2006; Usler et al., 2020).

Fast Period Visual Stimulation

While ERP research focuses on the neuronal-temporal correlates of, for instance, the processing of emotional facial expressions (Luck, 2014), more recent approaches seeks to exploit the frequency information encoded in the EEG signal (Rossion et al., 2015). For this reason, fast period visual stimulation (FPVS) paradigms were developed (Rossion et al., 2015). Comparable to classical ERP oddball paradigms, a deviant (e.g., an expressive face) is presented in a stream of repeating, standard stimuli (e.g., neutral faces) within an FPVS paradigm. Standard and deviant stimuli are not shown at the same frequency: The deviant (e.g., at the rate of 1.2 Hz) is presented less often than the standard stimulus (e.g., at the rate of 6 Hz). Neuronal responses can be measured in the same frequency ranges if the brain perceives these differences in stimulation (e.g., Dzhelyova et al., 2017). Thus, the FPVS approach is based on the assumption that a recurrent presentation of stimuli results in the same pattern of brain synchronization (Adrian & Matthews, 1934). It provides an implicit measure of facial expression processing, which is a significant advantage over explicit measures (e.g., response times or accuracy rates) because explicit measures are frequently biased in developmental samples due to inability to understand the task, general inhibition, or processing speed issues (Maguire et al., 2014). Regarding its use with preschoolers, the FPVS approach also allows to address some of the shortcomings of the ERP method: Younger populations have natural constraints in attentional resources, often leading to high loss of trials in EEG setups (e.g. due to movement, of up to 50%; Leppänen et al., 2007), which can affect the signal-to-noise ratio (SNR) and data quality (Luck, 2005). In contrast, the FPVS approach obtains robust brain responses after a very brief stimulation period (e.g., Dzhelyova et al., 2017) which can be also quantifiable at the individual level (Leleu et al., 2018). Moreover, whereas time windows for ERP amplitude analyses are frequently defined post-hoc (Luck & Gaspelin, 2017), frequency ranges within the FPVS method are determined prior to the experiment, allowing for simpler inter-study comparability. Lastly, the FPVS approach also allows to examine both frequency- and time-domain information (Dzhelyova et al., 2017; Leleu et al., 2018).

FPVS studies examining emotion recognition seek to determine whether the brain reacts to the abrupt change of a facial expression (e.g., from a neutral to an emotional expression, Leleu et al., 2018; van der Donck et al., 2020). In social interactions, where facial expressions are constantly changing, the ability to detect brief emotional changes in faces is pertinent to real-world situations (Schneider et al., 2022). First studies with adult and school-aged children samples detected a reliable response to a fast change in expression for various facial expressions (Dzhelyova et al., 2017; Leleu et al., 2018; van der Donck et al., 2020). Further, one study examined different emotion intensities for the deviant stimulus (e.g., 20% happy vs. 100 % happy expression; Leleu et al., 2018). The study revealed a linear increase in brain signal with increasing emotional arousal, suggesting that the brain is sensitive to the degree of emotional expression (Leleu et al., 2018). These findings pave the way for future research on the stability of emotion categories using FPVS. The use of the FPVS method with preschoolers has been limited to visual discrimination of faces from objects or individual features with robust and reliable deviant responses (Lochy et al., 2019). Thus, there are currently no FPVS-based studies that examine the affective processing of preschoolers.

1.3 Socio-emotional Competence Trainings for Preschoolers

The previous chapters illustrated the special nature of the preschool age for the socio-emotional competence development, particularly for emotion recognition, empathy, and prosocial behavior (Denham et al., 2009; Salerni & Caprin, 2022). Socio-emotional competence is an essential resilience factor for maintaining mental health and life satisfaction; therefore, the preschool years are the optimal time to promote the training of socio-emotional competence (Beelman, 2019). In terms of determining the effectiveness of a training, the gold standard for quantifying socio-emotional competence is the incorporation of multiple sources of behavioral measures (parent reports, observation and child assessment; Dirks et al., 2012; Mondi et al., 2021). Since changes following training in socio-emotional competence may not immediately translate into observable behavior (Blewitt et al., 2018), neuronal measures may provide insights into brain-level changes (Cicchetti & Gunnar, 2008; Leppänen et al., 2007). Particularly for basics of socio-emotional development such as facial expression processing, EEG techniques such as ERPs and FPVS appear to be excellent instruments for studying changes in young children (Batty & Taylor, 2006; Lochy et al., 2020). But to date, the incorporation of neuronal measures into the evaluation of the efficacy of a socio-emotional competence training has hardly been considered.

Firstly, this chapter begins with an overview of previous socio-emotional competence trainings, focusing primarily on classroom-based trainings and their challenges in implementation. The approach of digital, home-based trainings as an alternative to classroom-based trainings is then presented and supported by behavioral and neuroscientific studies.

1.3.1 Promoting Socio-Emotional Competence with Classroom-Based Trainings

In addition to the family as a socialization space (Roheger et al., 2022), preschool facilities are significant for the development of socio-emotional competence, which is why a variety of classroom-based, socio-emotional training programs exist (Egan et al., 2021; Mondi et al., 2021; Murano et al., 2020). Historically, socio-emotional competence trainings date back to behavioral theory-based interventions, which were first used in clinical settings and then increasingly in educational and preventive settings (Beelman, 2019). Nowadays, several programs specifically for preschool classrooms have been designed and evaluated (see L. Luo et al., 2022; Murano et al., 2020 for meta-analyses). They can be divided into (1) multi-component programs that target early childhood education holistically, including both the development of socio-emotional competence and the acquisition of other skills, and (2) skill-based programs that solely target the development of socio-emotional competence (Mondi et al., 2021). Two recent meta-analyses indicate that both categories of preschool programs have significant small to moderate effects (L. Luo et al., 2022; Murano et al., 2020). While these analyses focused primarily on U.S.-based programs, classroom-based training studies in Germany also detected improvements in emotion recognition and empathy (Wadepohl et al., 2011) as well as prosocial behavior (Koglin & Petermann, 2011; Lösel et al., 2006; Schick & Cierpka, 2006). In addition, programs can be distinguished according to their target population, with universal programs addressing all preschoolers and targeted programs addressing a specific population (e.g., children at risk for socio-emotional competence deficits; Murano et al., 2020). There is evidence that universal preschool programs are beneficial for all children, but children at risk may benefit less than their peers (Murano et al., 2020). The latter finding illustrates one of the primary drawbacks of classroom-based trainings: First, it is challenging to personalize and tailor the training material to each child's unique requirements (Mondi et al., 2021). Further, the frequency and duration of classroom-delivered trainings are typically preset, limiting the scope for customization. Lastly, the introduction of large-scale classroom-based programs necessitates substantial financial resources, infrastructure, and training of the teaching staff, which can impede the implementation of such programs in a sustainable manner (Adela et al., 2011; Mondi et al., 2021).

Establishing continuity of socio-emotional competence training components in both preschool and home settings has the potential to enhance the benefits for the child (Mondi et al., 2021; Murano et al., 2020). This argument is highlighted by the impact of the COVID-19 pandemic where most preschool facilities had to close with the onset of the pandemic (starting in March 2020 in Germany). For many children, the closure of preschool facilities led to severe isolation and social distancing from their peers, thereby halting their social-emotional development and worsening their mental health (Egan et al., 2021; Patrick et al., 2020). Home was the only environment in which children could pursue their education. These severe limitations in early childhood education emphasize the need for individualized, portable trainings that can be transferred to the home-learning environment of children. Particularly digital trainings (e.g., touchscreen application) seem to offer a promising alternative (Hollis et al., 2017).

1.3.2 Potential of Digital Socio-Emotional Competence Trainings

Due to the scarcity of financial and human resources and the difficulty of sustaining classroom-based trainings, offering socio-emotional competence trainings in home settings could be a promising alternative (Lehrl et al., 2021). Additionally, access to practice opportunities in both the preschool and home environments appears to be advantageous (Mondi et al., 2021). The circumstances of the COVID-19 pandemic heightened the significance of the family household as a learning environment (Egan et al., 2021). There is evident potential for digitally delivered home-based trainings: Digital media has become an integral element of children's daily lives (Herodotou, 2018; Hollis et al., 2020). In recent years, the use of digital media has increased rapidly among toddlers and preschoolers, particularly for interactive devices such as tablets and smartphones (e.g., about 72% of apps for touchscreen devices were aimed at young children; Herodotou, 2018). Besides digital applications tailored for purely entertainment purposes, a steep increase in digital interventions targeting mental health in children has been observed over the last years (Hollis et al., 2017). Particularly for socio-emotional competence trainings, tablet-based formats enable a visual presentation of naturalistic social learning environments (e.g., by integrating animations or video sequences of facial expressions or social interactions), which can contribute to authentic engagement with social situations (Wu & Kim, 2019). They may also enhance the motivation to learn new skills through persuasive design elements and gamified elements (e.g., engaging reward system; Whyte et al., 2015).

A first systematic review of the efficacy of digital applications for young children yielded few studies on digital socio-emotional competence training (Griffith et al., 2020). Compared to math-related digital trainings, the effects of socio-emotional trainings were smaller. The authors explained that it would be substantially more challenging to generalize socio-emotional competence to real-world scenarios (Griffith et al., 2020). In addition, all of the digital socio-emotional trainings of this review were focused on autistic children. However, it is considered increasingly important to expand the use of trainings from normalizing the behavior of children with pathologies (e.g., with socio-emotional competence deficits) and encouraging socio-emotional competence growth for all children (Mondi et al., 2021). Quantitative and qualitative studies with rather small sample sizes provide first evidence for the efficacy of digital socio-emotional competence programs for typically developing preschoolers ($N < 30$, e.g., Wu & Kim, 2019). Preschoolers, for instance, were able to transfer information from a gamified, interactive storytelling mobile application targeting anger management to their daily lives (Nicolaidou et al., 2022). Another study examined the effectiveness of the touchscreen application "The Empathy World" to foster children's empathy and prosocial behavior (Wu & Kim, 2019). The training group interacted with the application in a preschool classroom setting for five weeks and discussed its content after each session, whereas the control group participated in preschool classes as usual. Findings indicated that attention to others' feelings increased in the training, but not in the control group (Wu & Kim, 2019). A more recent study with a preschool sample reported higher levels of helping behavior towards the experimenter when playing prosocial touchscreen applications as compared to playing violent and neutral games beforehand (Shoshani et al., 2022). Nevertheless, there is a substantial shortage of randomized controlled trials systematically examining the effect of a socio-emotional competence training in typically developing preschool samples. In addition, the results to date are inconsistent and require cautious interpretation due to the small sample sizes and the emphasis on children with pathologies, which may not be applicable to typical development.

1.3.3 Evaluating Training Effectiveness With Behavioral and Neuronal Correlates

Digital socio-emotional training programs for preschoolers are still in their infancy of development. Accordingly, it is not surprising that the evaluation of these programs has focused primarily on behavioral measures (e.g., Nicolaidou et al., 2022; Shoshani et al., 2022). However, the inclusion of neuronal components is needed to better understand the brain mechanisms underlying the observed behaviors (Cicchetti & Gunnar, 2008). As described earlier, ongoing maturational processes lead to the refinement of cortical structures during childhood (e.g., prefrontal cortex; see chapter 1.2.2). At the same time, preschoolers become more sophisticated in their emotion recognition as well as empathic and prosocial behaviors (Denham, 2018, 2019). As shown in infant studies, brain correlates also facilitate the measurement of differences in processing of social stimuli which may not yet manifest in behavior or other report measures (e.g., Leppänen et al., 2007). Therefore, it provides the potential to investigate socio-emotional competence from various angles and thus place the findings in a larger context (Morales & Fox, 2019). Lastly, complementing behavioral with brain data may assist in distinguishing normative processes and behaviors from psychopathological development (Cicchetti & Gunnar, 2008).

The first study employing ERP measures in the context of a digital socio-emotional competence training for preschoolers examined the P2 component, which is sensitive to emotionally salient visual stimuli (Wu & Kim, 2019). Children of the training group showed a higher mobilization of attentional resources to harming situation, as indicated by a lower P2 amplitude, which, as the authors concluded, is more likely to lead to empathic concern or motivation directed at improving the well-being of the other (Wu & Kim, 2019). This finding contributes to the mapping of behavioral and neuronal correlates of training efficacy. Further research is required in which neuronal plasticity is closely examined in relation to changes in behavior.

1.4 Summary

Preschool is a crucial stage in the development of socio-emotional competence, as children navigate social situations with increasing independence. In this dissertation, I examined three fundamental components of socio-emotional competence: emotion recognition, empathy, and prosocial behavior, which become increasingly complex during early childhood. The maturity of these components can be mapped with behavioral measures. Research to assess maturity with neuronal correlates of ERP and FPVS has focused primarily on older age groups and pathological conditions. The preschool years and the onset of many mental disorders overlap. Since functional socio-emotional competence functions as a resilience factor in this context, the public health sector should prioritize the training of this competence. Numerous socio-emotional trainings for the classroom already exist, and their efficacy in fostering emotion recognition, empathy, and prosocial behavior has been demonstrated. However, there is a significant need for trainings that are applicable outside of the kindergarten environment. Particularly, digital trainings may present a significant opportunity due to their effective visualization tools and the widespread adoption of digital media among young children. However, there are few studies, some of which are qualitative only, that examine the efficacy of digital trainings. In addition, when assessing socio-emotional competence, examining changes in the brain and the complementary consideration of behavioral and brain measures are almost entirely absent.

2

Research Aims

I know every mile would be worth my while - I can go the distance.

From the Disney movie "Hercules" (1997)

2. Research Aims

The overarching purpose of this thesis was to elucidate preschool-relevant components of socio-emotional competence by investigating behavioral and neuronal measures in relation to their maturity and trainability. Study 1 and 2 focused on dissecting neuronal correlates related to socio-emotional competence, specifically examining the mechanism of emotion recognition from facial expressions. Study 3 assessed the trainability of both behavioral aspects and neuronal processes of socio-emotional competence, employing a social-emotional competence training which was carried out in children's home learning environment. In the following sections, I outline the scope of the respective studies based on the previously-reviewed literature.

2.1 Neuronal Mechanisms of Preschoolers' Emotion Recognition

Current research demonstrates the significance of preschool years for the normative development of socio-emotional competence (Denham et al., 2009; Salerni & Caprin, 2022). Emotion recognition from facial expressions is a fundamental building block for the development of more complex aspects of socio-emotional competence, such as empathy and prosocial behavior (Beauchamp & Anderson, 2010). According to behavioral studies, preschoolers perceive positive facial expressions more accurately and quickly than negative ones (Durand et al., 2007; Gao & Maurer, 2010; Sonneville et al., 2002).

In Study 1, we investigated how preschoolers encode and represent facial expression categories perceptually on a neuronal level. We employed a delayed match-to-sample-task that incorporated the repetition of different facial expressions (happy, angry, neutral). According to previous research with adult samples, the recurrent presentation of a facial expression leads to reduced ERP amplitudes, suggesting the reactivation of an existing memory trace or category of a facial expression (Campanella et al., 2002; Mueller et al., 2020). Therefore, we aimed to determine whether this also holds true for preschoolers, indicating the presence of fundamental facial expression processing mechanism. We hypothesized a decrease in amplitude in early (indexed by the P1 and N170) and late (measured with the P3) ERP components in response to repeated facial expressions, with happy expressions eliciting the largest amplitude reduction as they are most readily processed (Durand et al., 2007; Gao & Maurer, 2010; Sonneville et al., 2002). In addition, we correlated parental and child measures of emotion recognition and empathy with ERP data to determine if neural sensitivity to emotion repetition was associated with components of socio-emotional competence.

Naumann, S., Bayer, M., & Dziobek, I. (2022). Preschoolers' Sensitivity to Negative and Positive Emotional Facial Expressions: An ERP Study. *Frontiers in Psychology,* 13, 828066. https://doi.org/10.3389/fpsyg.2022.828066. *This is an open access publication.*

However, little is known about how the brain realizes these functions in preschool years, i.e., what are the neuronal-temporal trajectories of facial expression processing within this age range (Morales & Fox, 2019). Study 1 thus focused on the neuronal mechanisms of emotion discrimination and categorization examining ERPs of early and late processing. This study served as the basis for the generation of hypotheses for Study 2, in which we investigated whether and how preschoolers perceive rapid facial expression changes. In Study 2, we applied the FPVS approach (e.g., Rossion et al., 2015), which outputs high SNR brain responses, objectively identified in the frequency domain. Compared to ERP research, it provides a more fine-grained, rapid, and individual measure of emotion recognition, particularly relevant to developmental samples where task performance is often contaminated by motivational or decisional factors that are particularly difficult to control in young individuals (Dzhelyova et al., 2017; Lochy et al., 2019).

Collectively, we conducted Study 1 and 2 to further our understanding of the neuronal mechanisms underlying facial expression processing in typically developing preschoolers.

In Study 2, neuronal markers were quantified to assess preschoolers' ability to recognize facial expression changes. We employed two FPVS tasks to examine brain responses to (1) the discrimination of brief changes in facial expressions at maximum intensity (Dzhelyova et al., 2017) and (2) thresholds for the discrimination of gradual increasing facial expression intensities (Leleu et al., 2018). Given that preschoolers can reliably detect transient changes in facial expression, we hypothesized that this would be indicated by visible expression change responses (Lochy et al., 2020; Vettori et al., 2019). Secondly, we examined potential emotion processing differences: In accordance with previous FPVS literature (Dzhelyova et al., 2017), behavioral studies (e.g., Gao & Maurer, 2010), and findings from Study 1, we hypothesized that happy facial expressions would elicit larger responses than angry facial expressions. Thirdly, we assumed a linear increase in expression change response with increasing expression intensity. We were the first to test the FPVS approach with preschoolers to examine their emotion recognition abilities.

Naumann, S., Bayer, M., & Dziobek, I. (2022). Enhanced neural sensitivity to brief changes of happy over angry facial expression in preschoolers: A fast periodic visual stimulation study. https://doi.org/10.31234/osf.io/ucvkj
This is a preprint; the manuscript is currently under review.

2.2 Trainability of Behavioral and Neuronal Correlates of Socio-Emotional Competence

The fostering of functional socio-emotional competencies during preschool age represents a critical developmental task to prevent manifestations of psychiatric disorders and foster academic success (Beauchamp & Anderson, 2010; Beelman, 2019; Holodynski & Rüth, 2021). The evaluation of social-emotional competence training programs indicated positive outcomes for preschool classrooms (Mondi et al., 2021; Murano et al., 2020). Although trainings to promote socio-emotional competence in preschool settings are well-established (Beelman, 2019), there are few individualized approaches that children could use at home. Digital socio-emotional competence trainings, which have been infrequently systematically examined to date, could be a promising alternative (Hollis et al., 2017; Hollis et al., 2020). For the vast majority of studies examining the trainability of socio-emotional competence, behavioral measures are used to map developmental processes. The monitoring of neuronal mechanisms and their relationship to behavioral variables has been infrequent and has primarily concentrated on pathological development (Bayet & Nelson, 2019). **Consequently, we conceived of Study 3 to investigate the trainability of socio-emotional competence with behavioral measures and neuronal correlates, utilizing a digital socio-emotional competence training.** In addition to previous research (Kirst et al., 2022; Kirst et al., 2015), we based our paradigm, selection of ERP components, and hypotheses for our neuronal correlates on findings of Study 1:

Study 3 was a pre-registered randomized controlled trial to evaluate the efficacy of a digital socio-emotional competence training for typically developing preschoolers. We selected the touchscreen application Zirkus Empathico, which has been evaluated with autistic children as a digital training tool (Kirst et al., 2022; Kirst et al., 2015). Children practiced with Zirkus Empathico for six weeks in their home environment, while an active control group engaged with a digital foreign language training. We hypothesized that the training group compared to active controls would show greater improvements in social-emotional competence operationalized by parental reports and child assessments of emotion recognition, empathy, and prosocial behavior. As in Study 1 and 2, we were interested in the neuronal mechanisms related to emotion recognition from facial expressions. To quantify early (P1 and N170) and late (P3) ERP components, we employed a passive face viewing paradigm with various facial expressions (happy, angry, neutral) while collecting EEG. We hypothesized that P1, N170 and P3 amplitudes would be larger for the Zirkus Empathico group as compared to controls, indicative of attentional resources and greater emotional receptiveness dedicated to facial expression processing. In Study 3, we pioneered the systematic evaluation of the Zirkus Empathico training in preschoolers with behavioral and neuronal measures.

Naumann, S., Bayer, M., Kirst, S., van der Meer, E. & Dziobek, I. (2023). A randomized controlled trial on the digital socio-emotional competence training Zirkus Empathico for preschoolers. *npj Science of Learning.* 8, 20. https://doi.org/10.1038/s41539-023-00169-8 *This is an open access publication.*

3

Original Studies

Trials and tribulations, I've had my share

There ain't nothing gonna stop me now

'Cause I'm almost there.

From the Disney movie "The Princess and the Frog" (2009)

3. Original Studies

3.1 Neuronal Mechanisms of Preschoolers' Emotion Recognition: Study 1

Preschoolers' Sensitivity to Negative and Positive Emotional Facial Expressions: An ERP Study

Sandra Naumann, Mareike Bayer, Isabel Dziobek

Abstract: The study examined processing differences for facial expressions (happy, angry, or neutral) and their repetition with early (P1, N170) and late (P3) event-related potentials (ERPs) in young children (N = 33). EEG was recorded while children observed sequentially presented pairs of facial expressions, which were either the same (repeated trials) or differed in their emotion (novel trials). We also correlated ERP amplitude differences with parental and child measures of socio-emotional competence (emotion recognition, empathy). P1 amplitudes were increased for angry and happy as compared to neutral expressions. We also detected larger P3 amplitudes for angry expressions as compared to happy or neutral expressions. Repetition effects were evident at early and late processing stages marked by reduced P1 amplitudes for repeated vs. novel happy expressions, but enhanced P3 amplitudes for repeated vs. novel facial expressions. N170 amplitudes were neither modulated by facial expressions nor their repetition. None of the repetition effects were associated with measures of socio-emotional competence. Taken together, negative facial expressions led to increased neuronal activations in early and later processing stages, indicative of enhanced saliency to potential threating stimuli in young children. Processing of repeated facial expression seem to be differential for early and late neuronal stages: Reduced activation was detected at early neuronal processing stages particularly for happy faces, indicative of effective processing for an emotion which is most familiar within this age range. Contrary to our hypothesis, enhanced activity for repeated vs. novel expression independent of a particular emotion were detected at later processing stages which may be linked to the creation of new memory traces. Early and late repetition effects are discussed in light of developmental and perceptual differences as well as task-specific load.

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3.1.1 Introduction

During preschool age (3 to 5 years), children are increasingly exposed to opportunities for social learning, which is crucial for their socio-emotional development (Denham, 2006). One key facet of emotional competence constitues the ability to recognize different facial expressions, which is particularly important for communicating effectively with others (Denham, 2018). Emotion recognition from facial expressions follows different developmental trajectories (Gao & Maurer, 2010). Whereas young children seem to detect happy expressions with almost adult-like precision, they are less accurate for negative emotions such as anger or fear (Durand et al., 2007; Gao & Maurer, 2010). The relationship of quantitative and qualitative disparities in the development of emotion processing abilities during childhood remains a controversial topic. Some studies state that emotion recognition accuracy increases with age due to the progressive refinement of emotion categories (Johnston et al., 2011). Another line of research assumes that there is only a quantitative emotion processing difference due to emerging general cognitive abilities (McKone et al., 2012). Thus, the representation of facial expression categories may be difficult to discern with behavioral measures alone. Therefore, brain correlates such as event-related potentials (ERPs) are useful to examine how young children perceptually encode and represent facial expression categories on a neuronal level. The processing of facial expressions requires attentional resources which can be stimulus driven (e.g., Yantis, 1993) or top-down modulated (e.g., Hopfinger et al., 2000). Differences in the allocation of attentional resources can be observed at different neurophysiological stages during the processing of facial expressions (for review see Schindler & Bublatzky, 2020).

Across development, ERPs have been shown to successfully map early and late facial expression processing differences. Whereas infants' ERP waveforms seem to differ from adults' ERP morphology (e.g., due to physiological differences of the head; Leppänen et al., 2007) preschool age children already show a range of ERP responses evident in the adult literature on facial expression processing (Dennis et al., 2009). Initial and automatic detection of facial features is associated with early, sensory ERP components, like the P1 and N170, peaking at 100 ms and 170 ms respectively (Ding et al., 2017; Hinojosa et al., 2015). Since the low-level analysis of the face occurs at the P1 level, it has been shown to be influenced by a stimulus' motivational value (Rossi et al., 2017), spatial attention (Eimer et al., 2002) and physical properties (Schindler et al., 2021) . The N170 may be involved in the parallel and interactive processing of facial identity and expression (Hinojosa et al., 2015). In preschoolers, N170 and P1 ERP components were the most commonly reported neuronal responses to face and emotional faces stimuli (Bhavnani et al., 2021).

Subsequent in-depth face processing is associated with higher-order, later ERP components, like the P3, typically observed after 300 ms (Luo et al., 2010) and emerge during both passive face viewing and explicit attention tasks (see for review Schindler & Bublatzky, 2020). Though findings are heterogeneous, the majority of studies using passive face viewing paradigms showed that, in comparison to neutral facial expressions, positive and negative facial expressions led to increases in amplitudes of early and late components in infancy (Xie et al., 2019), in preschool- (Curtis & Cicchetti, 2011; Vlamings et al., 2010) and school-aged children (Anokhin et al., 2010).

Another branch of research investigated the neuronal categorization of facial expressions, presenting the same expression several times. In adults, the repetition of an identical facial expression led to a reduction in ERP amplitudes (Campanella et al., 2002).The repeated observation of a facial expression may re-activate an existing memory trace (e.g., emotion category associated with this facial expression) and thus ease its neuronal processing (Mueller et al., 2020). As a shift from low to high face processing proficiency is observed from infancy to school-age (Johnston et al., 2011; Watling & Damaskinou, 2018), young childhood seems to be a particular sensitive developmental period to establish refined facial expression categories. So far, however, facial expression categorization with repetition has not yet been investigated in young children. Studies investigating the repetition of facial identities reveal similar facilitating effects in infants, preschool and school-aged samples (Itier & Taylor, 2004; Lochy et al., 2020; Peykarjou et al., 2016; van Strien et al., 2011).

In order to examine neuronal differences in facial expression categorization in young children, we adapted an existing paradigm previously employed in infants to examine facial identity processing (Peykarjou et al., 2016). Within a delayed match-to-sample task, children saw two sequentially presented facial stimuli (hereafter: *Face 1* and *Face 2*) which were either identical or differed with regard to their facial expression (happy, angry, or neutral). Subsequently, children had to indicate whether Face 1 and Face 2 displayed the same or a different emotion. As compared to previous paradigms which integrated a repetition condition (e.g., He & Johnson, 2018), the experimental design included longer than usual stimulus' familiarization time to enable the creation of a reliable facial expressions representation as well as shorter time between stimuli to reduce cognitive load (Peykarjou et al., 2016; Schweinberger & Neumann, 2016). Although most prominent results were reported with paradigms in which face stimuli were repeated in a highly frequent or long-lagged manner (Campanella et al., 2002; van Strien et al., 2011), we chose a paradigm that repeated stimuli immediately and only once, which has also been shown to elicit reduced activation (Peykarjou et al., 2016; Turano et al., 2017).

In similar facial expression matching tasks, children's performance was better when facial expressions did not match, since non-matching expressions seem to be easier to detect than matching expressions (Sonneville et al., 2002). Thus, we expected children to be faster and more accurate when Face 1 and Face 2 showed different facial expressions. Additionally, we expected the highest accuracy rates and fastest reaction times for pairings with happy expressions (Sonneville et al., 2002). With regard to ERP responses, we predicted that amplitudes would be larger for emotional compared to neutral expressions. We expected happy expressions to elicit the largest amplitudes, followed by angry and neutral expressions (Curtis & Cicchetti, 2011; D'Hondt et al., 2017). Assuming that comprehensive facial expression representations are in place for young children, we expected an amplitude decrease in response to repeated facial expressions. Relative to angry or neutral expressions, we predicted that happy expressions would elicit the largest amplitude reduction because they are the most readily processed (Durand et al., 2007). In recent years, studies also reported links between early and late ERP responses to facial expressions and behavioral indexes of social-emotional processing (e.g., psychopathological traits; Hoyniak et al., 2019; Kujawa et al., 2012) and emotion regulation in preschool and school-aged children (Dennis et al., 2009). Thus, we also associated parental and child measures of socio-emotional competences (emotion recognition and empathy) with ERP data to assess whether they were related to larger ERP sensitivity regarding repetition effects.

3.1.2 Methods

Participants

We estimated a sample size of 34 participants with G*Power (Faul et al., 2007), assuming a medium to large effect size of $f^2 = 0.25$ for amplitude repetition effects (estimation based on experiment with similar paradigm of Peykarjou et al., 2016) and an attrition rate of 5% (similar to previous studies with young children; e.g., Gao & Maurer, 2010) for fixed effects in linear multiple regression to provide 80% power at a two-sided 5% α-level. The total sample consisted of 33 children aged 4- to 6-years. One participant was excluded for non-compliance during the EEG recording and one participant due to non-visibility of the ERP components (non-visibility due to below 10 trials per condition) leaving a final sample of 31 children ($M = 5.14$ years, $SD = 0.67$, 15 females). Participants were recruited from an existing university database. As compensation, families were paid € 16. All children showed normal intellectual functioning and receptive verbal ability as assessed by the Peabody Picture Vocabulary Test 4th Edition (PPVT-4; Dunn & Dunn, 2007) and Columbia Mental Maturity Scale (CMM; Eggert, 1972). We also screened for abnormalities in social ability with the Social Responsiveness Scale (SRS; Constantino & Gruber, 2005) and Social Communication Questionnaire (SCQ; Rutter et al., 2003) None of the children exceeded the cut offs indicative of social impairments. Demographics included family income, caregiver occupation and education, which were summarized to a socioeconomic score (SES; Winkler index; Winkler & Stolzenberg, 1998; range: 3-15, low SES = 3-6, medium SES = 7-10, high SES = 11-15). Families' socioeconomic status ranged from middle to upper class. Screening and demographic information is described in Table 3.1.1.

The study protocol was reviewed and approved by the ethics committee of the Department of Psychology at Humboldt-Universität zu Berlin. The study was conducted in accordance with the Declaration of Helsinki. Informed consent for study participation was given by a parent prior to testing.

Table 3.1.1 Participant demographics and characteristics.

Variables	Age (yrs)	SES	PPVT	CMM	STM	SRS	SCQ
Mean	5.14	11.77	58.46	60.13	44.68	35.03	4.26
SD	0.67	2.26	27.39	36.31	6.08	12.70	2.08

Note. SES, Socioeconomic status; PPVT, Peabody Picture Vocabulary Test; CMM, Columbia Mental Maturity Scale; STM, Short-term Memory; SRS, Social Responsiveness Scale; SCQ, Social Communication Questionnaire.

Stimuli and Procedure

Stimuli consisted of happy, angry, and neutral facial expressions of 36 males and 36 females from standard face databases (Radboud Faces Database; Langner et al., 2010; Chicago Face Database; Ma et al., 2015). All face stimuli were grey-scaled and trimmed to the same oval shape to exclude hair and non-facial contours (height: 150 pixels, width: 110 pixels). Mean luminance levels were measured and adjusted for all stimuli. We calculated stimulus contrast values employing MATLAB R2016b ("MATLAB," R2016b) toolboxes graycomatrix and graycoprops. We detected differences of contrast across emotion conditions ($F(2,215) = 26.08$, $p < .001$) with happy expressions having larger contrast values than angry ($p < .001$) or neutral expression ($p < .001$). Thus, to statistically control for low-level differences in stimulus contrast, we entered the individual stimulus contrast as additional covariate as well as stimulus as random intercept in all ERP analyses. Stimuli were presented on a grey background (RGB = 100, 100, 100) on a 15`` monitor (display resolution: 1024 x 767) that was positioned at a distance of approximately 70 cm from the participant (visual angle: 3.27°).

On the day of children's testing, families were given a brief tour of the laboratory, received information about the testing and were given the opportunity to ask questions. Thereafter, parents signed a consent form for their children's participation in the study. During cap placement and recording, parents filled out questionnaires regarding their socioeconomic status and their children's socio-emotional competences. Recording sessions took place in an electrically shielded and sound-attenuated booth. Children's looking behavior was monitored using a video camera. One experimenter was seated next to the child during the testing to assist in directing its attention to the presentation screen.

As shown in Figure 3.1.1, a trial consisted of two faces of the same identity (Face 1 and Face 2). Face 1 was either followed by a Face 2 with the same facial expression (repeated trial) or a different facial expression (novel trial). As an example, novel happy trials could either contain an angry or neutral expression as Face 1, but Face 2 was always a happy expression. In contrast, a repeated happy trial contained a happy expression at both Face 1 and Face 2. Each trial was set up as follows (Peykarjou et al., 2016): A fixation cross was presented for 500, ms which was followed by a jittered inter-stimulus interval (ISI; 400-600 ms) and Face 1 (1,500 ms). After another jittered ISI (500-700 ms), Face 2 (1,500 ms) was presented. At the end of a trial, children had to indicate whether the facial expression of Face 1 and Face 2 matched. They had a small button box with one button in each hand. On screen, formation of triangles and squares served as reminders of the button order (e.g., two squares on the left side indicated that the button in the left hand needed to be pressed when the facial expression of Face 1 and Face 2 was repeated). The button order was counterbalanced. Between trials, there was a jittered inter-trial interval (ITI) of 1,000-1,500 ms. There were 3 blocks with 48 trials each, summing up to a total of 144 trials. Within blocks, no condition, gender or valence was repeated more than three times successively. Face identity was never repeated within a block and maximally repeated twice throughout the whole paradigm. Face gender was equally distributed across blocks. For each valence (happy, angry, neutral), there were 16 trials per block, half of them repeated, which resulted in 24 repeated and 24 novel trials. Participants were instructed to keep their gaze at the center of the presentation screen. In order to guarantee that the children paid attention, an animal cartoon picture would appear randomly at the location of the face stimuli after some face trials. Participants were told that if they spotted all animals and pressed a button at their appearance, they would get to see all animals integrated into a nature scene after each block. A short practice session with 4 practice trials preceded the actual test session. During the EEG task, we also recorded reaction times and accuracy. The task was administered using Presentation® software (Version 17.2, Neurobehavioral Systems, Inc., Berkeley, CA, www.neurobs.com). After the recording session, children's intellectual and verbal functioning as well as emotion recognition and empathic skills were assessed.

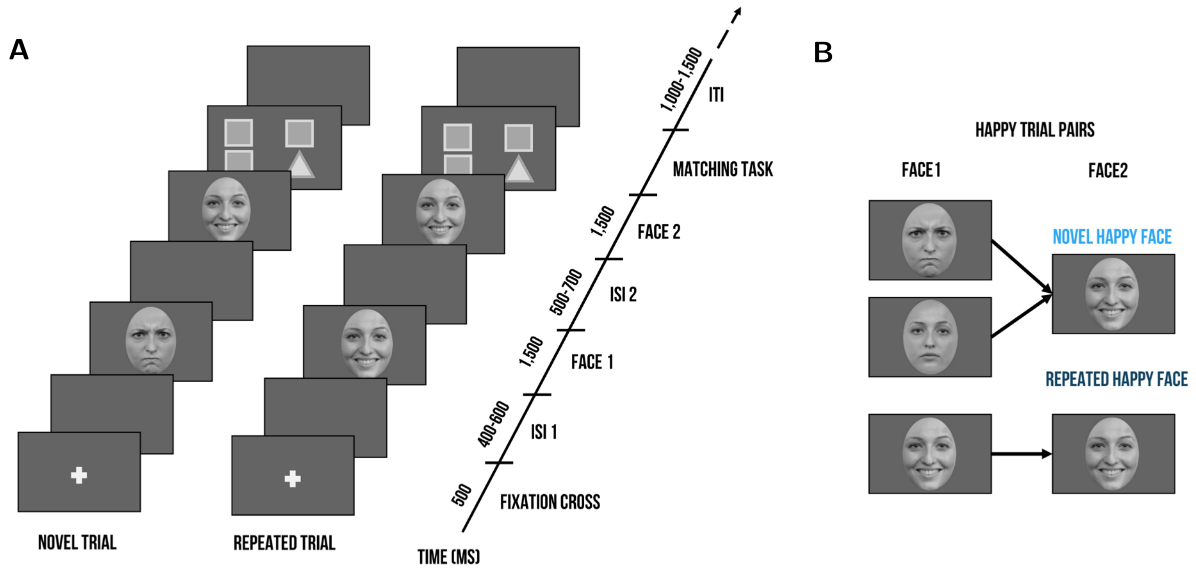


Figure 3.1.1 Visualization of emotion priming paradigm with delayed match-to-sample-task. (A) Exemplary trial sequence: Each trial included the presentation of a fixation cross (500 ms), followed by a blank screen (400-600 ms), Face 1 (1,500 ms), another blank screen (500-700 ms) and Face 2 (1,500 ms). Face 2 could either bear the same facial expression as Face 1 (*repeated trial*) or a different one (*novel trial*). After seeing Face 2, children had to indicate whether the facial expression of Face 1 and Face 2 were the same; triangles and squares shapes on screen served as reminders of the button order (e.g., two squares on the left side indicated that the left button needed to be pressed when the facial expression of Face 1 and Face 2 was repeated). (B) Exemplary trial pairs for happy expressions. *Novel* happy face trials started with a neutral or angry expressions at Face 1 and always contained a happy expression at Face 2. *Repeated* happy face trials consisted of the same happy facial expression at Face 1 and Face 2.

Emotion recognition and empathy measures

We employed an emotion matching task (EMT; Watling & Damaskinou, 2018) using the facial stimuli of the delayed match-to-sample task. Children saw a pair of faces of the same identity but with a different facial expression (happy, angry, neutral). Both faces were presented at the same time. While faces were on screen, children heard a voice-over of an emotion word (happy, angry, or neutral). They had to indicate by button press which of the faces (left or right) matched the voice-over. Facial expressions were equally distributed as well as randomized and the button-order was counterbalanced. The EMT served as a counterpart to the delayed match-to-sample task to examine whether children could correctly identify the different facial expressions and to provide an additional set of behavioral measures (reaction times and accuracy).

We assessed children's emotion recognition and empathy skills with the *Inventory to survey of emotional competences for three- to six-year-olds* (EMK 3-6; Petermann & Gust, 2016). The EMK 3-6 shows good internal consistency (Cronbach's Alpha = .78-.90) as well as validity (Gust et al., 2017). It includes a parental questionnaire and child assessments to evaluate socio-emotional competences. Children had to identify other children's emotions on picture cards and explain why children might feel that particular way. As for the empathy task, they were asked to imagine themselves in emotionally charged situations through a doll's perspective (e.g., the doll is afraid of dogs, what happens if the doll meets a dog?) and come up with coping strategies (e.g., to chase the dog away). Composite z-scores were calculated for parental ratings and child assessment.

Short-term memory task

We included a short-term memory task to control for children's general cognitive abilities, which required the child to recite numbers (Esser & Wyschkon, 2016). The examiner would name a sequence of numbers and ask the child to repeat them in the same order. The first sequence started with two numbers and progressed to up to nine numbers. The examiner stopped the task when the child was not able to recite the numbers after the examiner had repeated them twice. Points were administered for each round (2 points if child repeated numbers without help, 1 point if child needed to hear digits twice) and summed into one score. Sum scores where transformed into standardized scores by using children's age.

EEG Recording, Processing, and Analysis

EEG signals were collected with the QRefa Acquisition Software, Version 1.0 beta (MPI-CBS, Leipzig, Germany) from 46 Ag/AgCl electrodes attached to elastic caps (EasyCap GmbH, Germany) at standard positions and synchronized with the onset of stimulus presentation. Electrode impedances were kept below 10 kΩ. Digitalization of the EEG data was carried out continuously at a sampling rate of 500 Hz (anti-aliasing low pass filter of 135 Hz). EEG recordings were referenced online to CZ with the ground electrode at FP1. Electro-oculograms were registered with electrodes at the outer canthi of both eyes and at the orbital ridge of the right eye.

Further offline pre-processing and analyses were carried out in MATLAB R2016b using EEGLAB (Delorme & Makeig, 2004) and the toolboxes SASICA (Chaumon et al., 2015) and ERPLAB (Lopez-Calderon & Luck, 2014). Data were high-pass filtered at 0.01 Hz and low-pass filtered at 30 Hz with an IIR Butterworth filter (2^{nd} order) as well as a Parks-McClellan Notch filter at 50 Hz. EEG data were re-referenced to the average of all data channels (excluding eye channels) and segmented from 200 ms before stimulus onset to 1,500 ms post-stimulus onset. Baseline correction was based on the mean activity during the 200 ms prior stimulus onset. We manually removed non-systematic noise (e.g., pulling the cap) to improve the succeeding independent component analysis (ICA) for ocular artifact removal. SASICA was then used to mark and reject the detected ocular artifacts. Afterwards, segments that still contained artifacts were manually rejected on the base of a semi-automated artifact rejection with a voltage criterion (exceeding $\pm$ 200 μV) and visual inspection of each trial. After artifact rejection, the mean number of trials per condition was not significantly different for facial expressions (happy: $M = 39.9$, $SD = 6.2$, angry: $M = 39.5$, $SD = 6.5$, neutral: $M = 39.4$, $SD = 5.9$; $F(2, 90) = 0.83$, $p = 0.44$). Trial numbers for repeated trials ($M = 58.2$, $SD = 9.1$) were significantly lower compared to novel trials ($M = 60.6$, $SD = 9.0$; $t(30) = 5.0$, $p < 0.001$). Please note that further trials were removed within the statistical analysis due to reaction time exclusion criteria, for final trial numbers and statistics see below.

Regions of interest for the ERP components and time windows were based on previous research (Batty & Taylor, 2006; Curtis & Cicchetti, 2011) as well as visual inspection of the ERP topographies averaged across all conditions and participants. Previously, P3 responses have been found to be maximal over parietal locations (e.g., Kujawa et al., 2012). Within our sample, however, visual inspection of topographies across all conditions showed maximal activation over more parieto-occipital sensors (previous studies with young children also chose sensors at more occipital or parietal-occiptal sensors: e.g., Curtis & Cicchetti, 2011; MacNamara et al., 2016; Vlamings et al., 2010). Thus, ROIs for P1 and P3 were composed of the electrodes PO3, O1, PO7, Oz, O2, PO4 and PO8.In a parallel fashion, maximal N170 responses have been typically observed at parietal-occipital regions (e.g., Rossion & Jacques, 2008). Visual inspection showed slight diversion from the literature: we chose a left temporal-parietal cluster (P7, TP7, CP5) and a right temporal-parietal cluster (P8, TP8, CP6) to score the N170. The electrode layout is demonstrated in Figure 3.1.2. P1 and N170 peaks for each participant were identified using peak detection procedures and quantified as mean amplitude in a time window of 20 ms around the peak. P1 peaks were determined in the time window of 90 to 130 ms; N170 peaks in the time window of 180 to 220 ms. The P3 was quantified in the time window of 300 to 500 ms. Time windows are comparable to previous ERP studies examining preschool samples (e.g., Dawson et al., 2004; D'Hondt et al., 2017).

Statistical analyses

Statistical analyses were performed using R-Studio (R Core Team, 2019). For all analyses, we excluded trials with reaction times (RTs) lower than 250 ms (Johnston et al., 2011) and incorrect trials (Langeslag et al., 2020). Neither the final number of trials for each facial expression (happy: $M = 33.5$, $SD = 6.85$, angry: $M = 32.7$, $SD = 7.27$, neutral: $M = 33.3$, $SD = 8.09$; F(2,

87) = 0.1, $p = 0.91$) nor for repeated ($M = 50.1$, $SD = 14.6$) vs. novel trials ($M = 49.4$, $SD = 13.7$) differed significantly ($t(29) = 0.2$, $p = 0.9$).

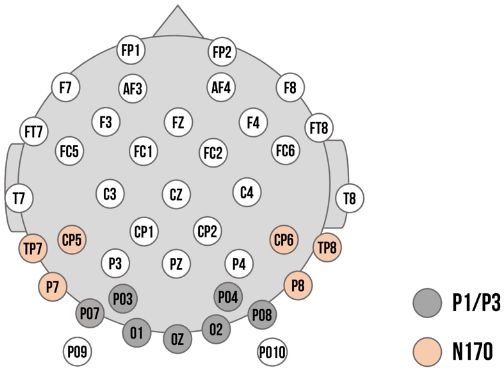


Figure 3.1.2 Electrode montage with channel locations used as regions of interest (ROIs). Dark grey: Channels used for the P1 and P3 component. Orange: Channels used for the left and right cluster for the N170 component.

All (general) linear mixed model analyses were conducted with the lme4 package (Bates et al., 2015). Assumptions for multiple regression were checked for all models (normality of the residuals, linearity, multicollinearity, homoscedasticity). Marginal and conditional R^2 were calculated as measures of goodness of fit for mixed models, in which marginal R^2 reflects variance explained by fixed factors, and conditional R^2 variance explained by the entire model. The p-values (uncorrected) were computed via Wald-statistics approximation (treating t as Wald z); interaction effects were delineated with post-hoc tests (multcomp package; v1.4-16, Hothorn et al., 2008). As first fixed factor, we included a contrast for repetition (novel vs. repeated trials; contrast coding: [-0.5, 0.5]). Further, we defined two contrasts to compare effects between facial expressions: The first contrast disentangled the averaged effect of both emotional expressions compared to neutral expressions (emotional [average of happy/angry] vs. neutral expressions; contrast coding: [-0.25, -0.25, 0.5]), while the second contrast compared the effect of happy vs. angry expressions (contrast coding: [0.5, -0.5 ,0]). We also included the interaction between facial expressions and repetition contrasts as fixed factor. Short-term memory scores were entered as a scaled covariate in all (G)LMM analyses to control for cognitive task demands. As random intercepts, we included participant and facial stimulus.

For the delayed match-to-sample-task, we calculated a general linear mixed model (GLMM) for accuracy rates and a linear mixed model (LMM) for RTs. Additionally, RTs were log-transformed (determined with the Box-Cox procedure; Box & Cox, 1964) to meet the assumption of normally distributed residuals. Regarding the ERP components, we focused on neuronal responses to Face 2 employing linear mixed models and including physical stimulus contrast as additional scaled covariate to control for low-level differences, as well as electrode as additional random intercept. Results for Face 1 are reported in the supplement. As hemispheric differences were previously reported for the N170 component (Batty & Taylor, 2006), we also included hemisphere as fixed factor for the N170 analysis (left vs. right ROI).

For the EMT, we only applied the facial expression contrast within a GLMM for accuracy rates and an LMM for RTs. We only report findings for short-term memory or stimulus contrast if found to be significant (see Supplementary Material for full model statistics). Lastly, we performed correlational analyses using Pearson's correlations to associate brain and behavior variables. For significant ERP modulations by facial expression and repetition, we calculated amplitude difference scores between conditions and correlated them with the composite scores of empathy and emotion recognition. We used the false discovery rate (FDR) to correct for multiple comparisons in post-hoc tests and correlational analyses.

3.1.3 Results

Delayed match-to-sample-task performance

As displayed in Figure 3.1.3, there were no accuracy differences for facial expression contrasts (emotional vs. neutral expressions: $\beta < 0.01$, $p = 0.97$, $OR = 1.00$ [95% CI: -0.65, 2.65]; happy vs. angry expressions: $\beta = -0.17$, $p = 0.07$, $OR = 0.85$ [95% CI: -0.55, 2.24]) or repetition ($\beta = -0.01$, $p = 0.95$, $OR = 0.99$ [95% CI: -0.64, 2.63]). Interactions between facial expression contrasts and repetition yielded no significant results (emotional vs. neutral expressions x repetition: $\beta = 0.23$, $p = 0.29$, $OR = 1.25$ [95% CI: -0.81, 3.32]; happy vs. angry expressions x repetition: $\beta = 0.26$, $p = 0.17$, $OR = 1.30$ [95% CI: -0.84, 3.43]).

For reaction times, the emotional vs. neutral facial expression contrast yielded no significant results ($\beta = 0.05$, $p = 0.31$). In line with our hypothesis, happy faces were detected faster than angry faces ($\beta = 0.09$, $p = 0.03$), indicating that the correct identification of a Face 2 with a happy expression as either repeated or novel was faster than for a Face 2 with an angry expression. The main effect for repetition was not significant ($\beta = -0.02$, $p = 0.59$). The interaction of emotional vs. neutral expressions with repetition, however, was significant ($\beta = -0.20$, $p = 0.03$). Novel happy faces were detected faster than novel neutral faces ($p = 0.01$), suggesting that, irrespective of what was presented as Face 1, when Face 2 showed a novel happy expression, it was faster identified correctly as novel compared to a novel neutral face. None of the other post-hoc tests were significant (all $p > 0.75$). Similarly, the interaction of happy vs. angry expressions with repetition was not significant ($\beta = -0.11$, $p = 0.19$; see Supplementary material table S3.1.1-S3.1.2).

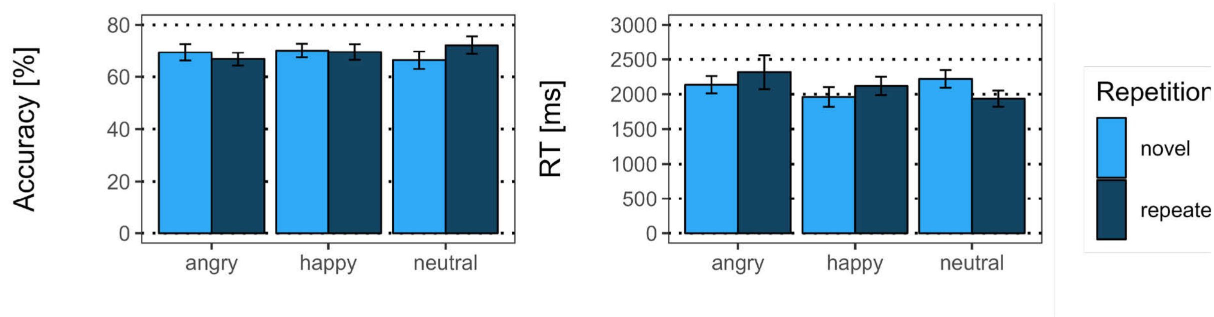


Figure 3.1.3 Accuracy rates and reaction times of the delayed match-to-sample task. Error bars indicate standard errors (SE).

ERP responses

P1

In line with our hypothesis, we found larger P1 amplitudes for emotional vs. neutral expressions ($\beta = -1.29$, $p = 0.001$; Figure 3.1.4-3.1.5 and Figure S3.1.1 of the Supplementary material). Both happy ($p = 0.003$) and angry expressions ($p = 0.03$) elicited larger P1 amplitudes compared to neutral expressions. No amplitude differences were detected between happy and angry expressions ($\beta = -0.27$, $p = 0.44$). There was no main effect of repetition ($\beta = -0.11$, $p = 0.73$). Similarly, no interaction of emotional vs. neutral expressions with repetition was found ($\beta = 1.20$, $p = 0.14$). We did, however, detect a significant interaction of happy vs. angry expressions with repetition ($\beta = 2.75$, $p < 0.001$): Post-hoc tests indicated that, in line with our hypothesis, P1 amplitudes for repeated happy expressions were smaller than for novel happy expressions ($p = 0.003$). Novel happy expressions elicited larger P1 amplitudes than novel angry expressions ($p = 0.005$; all other $p > 0.12$; see Supplementary Material table S3.1.3-S3.1.5).

N170

We did not find significant main effects for facial expression contrasts (emotion vs. neutral expressions: $\beta = -0.08$, $p = 0.83$; happy vs. angry expressions: $\beta = 0.11$, $p = 0.75$) or repetition ($\beta = 0.07$, $p = 0.80$). None of the interactions of facial expressions with repetition were significant (emotion vs. neutral expressions: $\beta = 0.87$, $p = 0.43$; happy vs. angry expressions: $\beta = 1.16$, $p = 0.08$, see Supplementary Material table S3.1.3).

P3

In line with our hypothesis, we detected differences for emotional vs. neutral facial expressions (β = -1.05, p = 0.02). Angry expressions elicited larger P3 amplitudes than neutral expressions (p = 0.001) and happy expressions (β = 1.10, p = 0.004). No significant difference was found for happy vs. neutral expressions (p = 0.77). In contrast with our hypothesis, we detected a significant main effect of repetition, indicating that repeated faces elicited larger P3 amplitudes than novel faces (β = 0.88, p = 0.014). Interactions of facial expression contrasts with repetition were not significant (emotional vs. neutral facial expressions x repetition: β = 0.73, p = 0.42; happy vs. angry facial expressions x repetition: β = -0.78, p = 0.32). Additionally, we detected that stimulus' contrast was a significant covariate, with larger contrast values eliciting larger P3 amplitudes (β = -0.50, p = 0.03, see Supplementary Material table S3.1.3 & S3.1.6). All ERP results for Face 1 (examining facial expression contrasts) are reported in the supplement (see Supplementary Material table S3.1.7- S3.1.9).

Emotion recognition and empathy measures

Emotion matching task (EMT) performance

There were no accuracy differences between emotional vs. neutral expressions (β = 0.10, p = 0.62, OR = 1.10 [95% CI: -0.71, 2.92]) or happy vs. angry expressions (β = 0.33, p = 0.05, OR = 1.39 [95% CI: -0.90, 3.69]). For reaction times, the emotional vs. neutral expression contrast was significant (β = 0.11, p = 0.01). Post-hoc tests indicated that happy expressions were detected faster than neutral expressions (p = 0.01; angry vs neutral: p = 0.18). The happy vs. angry contrast yielded no significant results (β = 0.05, p = 0.19, see Supplementary Material table S3.1.10 & S S3.1.11).

ERP associations with socio-emotional competence measures

We calculated difference scores of significant facial expression x repetition interactions (novel happy-repeated happy, novel happy-novel angry) for P1 amplitudes and a difference score for the P3 main effect of repetition (novel-repeated). Subsequently, we associated them with EMK 3-6 empathy and emotion recognition composite scores. None of the correlations of emotion recognition or empathy with P1 or P3 difference scores survived FDR-correction (all $p > .63$, see Supplementary Material table S3.1.12 & S3.1.13).

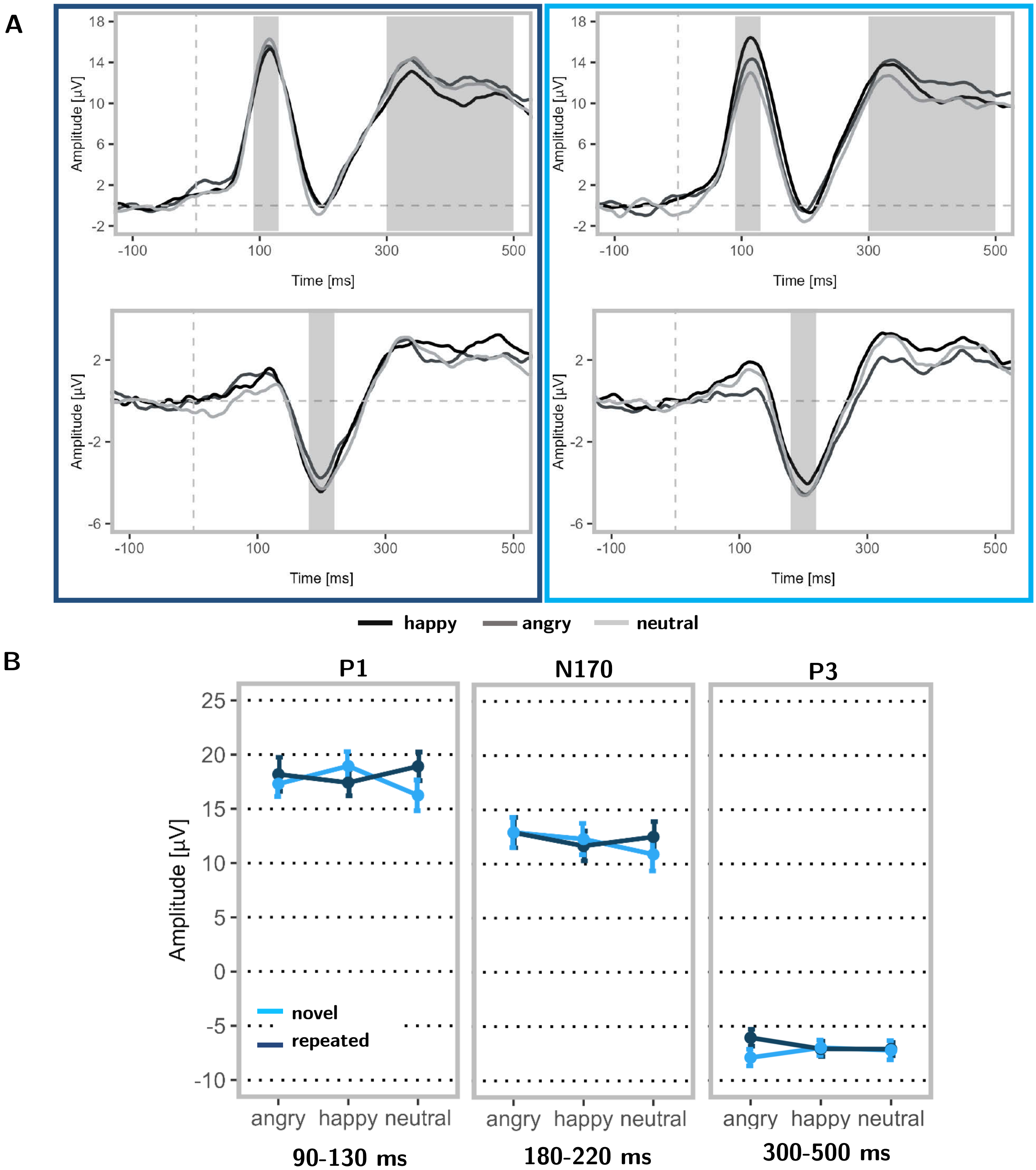


Figure 3.1.4 ERP waveforms and mean amplitudes at Face 2. (A) Upper left: Grand-averaged P1 and P3 waveforms for repeated happy (black), angry (dark grey), and neutral (light grey) facial expressions (ROI: PO3, PO4, PO7, PO8, O1, O2, Oz). Upper right: Grand-averaged P1 and P3 waveforms for novel facial expressions. Bottom left: Grand-averaged N170 waveforms for repeated happy, angry, and neutral facial expressions (ROI: P7, TP7, CP5, P8, TP8, CP6). Bottom right: Grand-averaged N170 waveforms for novel facial expressions. Shadowed areas indicate the time windows used to identify participants' individual peaks and mean amplitudes. (B) Mean P1, N170, and P3 amplitudes and standard deviations separately for each condition.

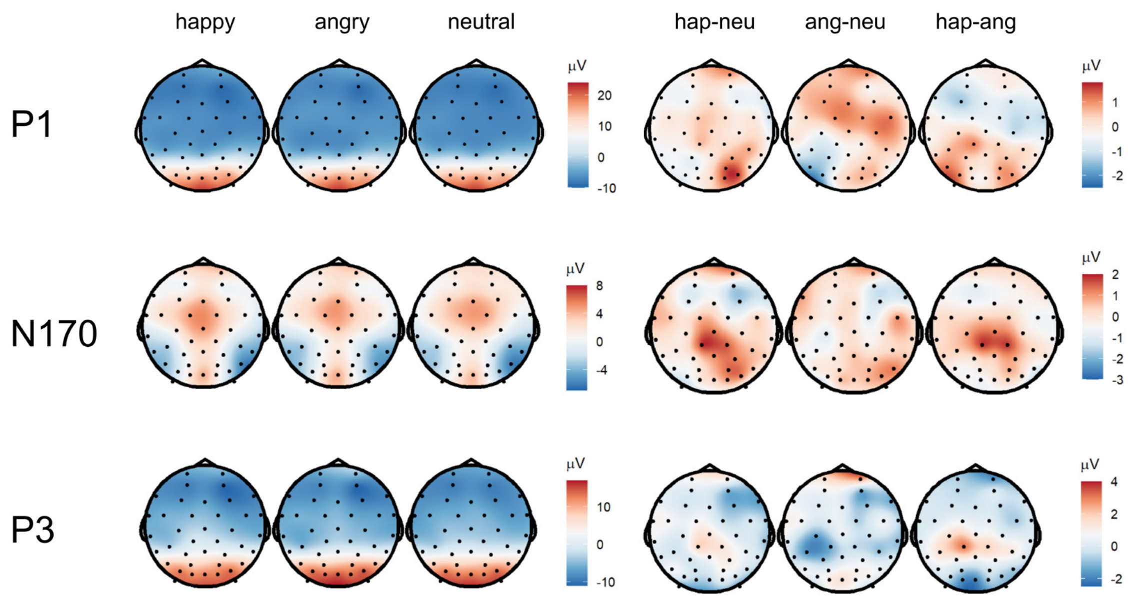


Figure 3.1.5 Topographies of the averaged P1 (90-130 ms), N170 (180-220 ms) and P3 (300-500 ms) activity displaying scalp topographies and difference topographies (in µV) for the emotion condition.

3.1.4 Discussion

Our study sought to provide further evidence on young children's neuronal representation of facial expressions. To this aim, we employed a delayed match-to-sample task in which two faces (Face 1, Face 2) of the same identity were presented in succession, either displaying the same (repeated trial) or a different (novel trial) facial expression. Subsequently, children were asked to indicate whether facial expressions of Face 1 and Face 2 matched. We assessed neuronal representations with ERPs of early (P1, N170) and late (P3) facial expression processing. Additionally, we examined reaction times and accuracy rates as well as associations with measures of socio-emotional competence (emotion recognition and empathy). In line with our hypothesis, we found that, independent of repetition, correct match/mismatch decisions were fastest when Face 2 was happy as compared to angry. For novel trials, correct match/mismatch decisions were also faster when happy vs. neutral expressions were presented as Face 2. Additionally, the EMT indicated that happy expressions were detected faster than neutral expressions. As hypothesized, modulations by expressions were found for early and late ERPs. However, no overall advantage of happy expression was apparent: P1 amplitudes were larger for angry and happy expressions as compared to neutral expressions. P3 amplitudes were larger for angry compared to happy and neutral expressions. Repetition effects were visible at early and late processing stages: We found reduced P1 amplitudes for repeated happy expressions as compared to novel happy expressions.

Additionally, novel happy expressions elicited larger P1 amplitudes than novel angry expressions. In contrast to our expectations, we detected larger P3 amplitudes for repeated compared to novel facial expressions. None of the repetition effects were associated with measures of socio-emotional competence.

Emotion modulation in early and late ERPs

In line with our hypotheses, we detected larger amplitudes for emotional vs. neutral expressions in early and late ERP responses. Modulations by facial expressions, however, slightly diverted from what we had predicted. For early ERPs, we found larger P1 amplitudes for happy and angry as compared to neutral expressions, but no differences between happy and angry expressions (effect also detected at Face 1, see Supplementary Material table S7 & S8). With reference to previous research, some studies showed P1 amplitude differences between happy and angry expressions (D'Hondt et al., 2017), while others also reported comparable ERP responses (Batty & Taylor, 2006; Todd et al., 2008). Former studies mostly employed passive viewing tasks to discern differences in children's facial expression processing, whereas our task asked children to actively match facial expressions, potentially influencing ERP responses. Thus, even though happy facial expressions seem to be most readily processed (Sonneville et al., 2002), task demands might have led to a shift in saliency and attentional resources.

Our null results concerning the N170 are in line with some of the previous research, which did not report ERP modulations by happy or angry vs. neutral expressions in preschoolers (Dennis et al., 2009; Todd et al., 2008). The N170 component has been discussed to be more involved in facial structural encoding than in emotion detection, which is indicative of two parallel but independent stages of face processing (V. Bruce & Young, 1986). The N170 is also undergoing significant maturational changes (e.g., from bifid to unified trajectory; Batty & Taylor, 2006). Thus, the averaging process across children who show great N170 variability may have also diminished potential effects.

For late ERP responses, we detected larger P3 amplitudes for angry expressions as compared to happy or neutral expressions (effect also detected at Face 1, see Supplementary Material table S7 & S9), which might suggest more in depth-analysis of negative facial expressions in young children. Firstly, emotions with negative valence such as fear or anger represent salient evolutionary value because they provide cues to retreat or prepare to defend oneself (Gao & Maurer, 2010). Therefore, larger amplitudes for angry vs. happy expressions may be indicative of a prioritization in processing of potentially stimuli (D'Hondt et al., 2017; Xie et al., 2019). Secondly, young children are less familiar with angry expressions, which has been shown in behavioral studies suggesting a protracted development of reliably detecting angry facial expression until later childhood (Gao & Maurer, 2010). Considering typical social environments during preschool time, expressions of anger might be quite novel and less frequent. An example of how environment shapes emotional development is discussed by one study who reported that children formerly exposed to high levels of parental anger recognized this emotion earlier than children of the control group (Pollak et al., 2009). These findings might explain why P3 amplitudes were largest for angry expressions. Regarding the null findings for P3 amplitude differences between happy vs. neutral expressions, one has to note that, before the age of nine, children often rate neutral faces as happy or sad (Durand et al., 2007). Thus, during in depth-face processing similar amplitudes might have been elicited for happy and neutral expressions.

Repetition effects in early and late ERPs

In line with our hypothesis, we detected reduced P1 amplitudes for repeated happy as compared to novel happy trials, which may be suggestive of decreased processing efforts and re-activations of existing memory traces particularly for happy expressions in young children (Nordt et al., 2016). In contrast, we did not find reduced P1 amplitudes for repeated angry or neutral as compared to novel angry or neutral expressions. Thus, neuronal representations for these facial expressions might not be as developed yet. This is in line with previous research indicating that happy expressions are most readily processed (Durand et al, 2007), whereas protracted trajectories have been found for angry or neutral expressions (Gao & Maurer, 2010). This ERP result is also paralleled by our reaction times findings of the EMT and delayed match-to-sample task indicating faster reaction times for pairings with happy expressions. In concordance, other studies also reported that the presence of happy faces facilitates the matching of emotion pairs (Sonneville et al., 2002). Besides faster reaction times for happy vs. angry expressions in the delayed match-to-sample task, we also detected larger P1 amplitudes for novel happy as compared to novel angry expressions.

Alternatively, since we had stimulus contrast differences indicating larger contrast values for happy faces, it is possible that the P1 response was influenced by low-level stimulus differences. Previous studies indicated that the P1 is influenced by low-level stimuli changes (e.g., Rossion & Caharel, 2011; Schindler et al., 2021). There is, however, another research branch indicating that changes in low-level stimulus' characteristics do not always suffice to cause P1 modulations (Dering et al., 2011; Dering et al., 2009). Recently, it was concluded that pure low-level accounts do not seem to fully explain P1 modulations in response to emotional stimuli, favoring accounts that propose a mixture of bottom-up and top-down processes to be indexed by the P1 (Bruchmann et al., 2020; Klimesch, 2011). Within an integrative review examining emotional face processing in ERPs, it was also argued that top-down and emotional bottom-up relevance do not act in isolation but can be regarded as interconnected phenomena (Schindler & Bublatzky, 2020). Additionally, we have controlled for stimulus' differences by including both a random intercept for every stimulus and individual contrast values as covariate in order to minimize the impact of perceptual features on our effects.

While we detected first evidence at the level of the P1 for reduced processing efforts for repeated facial expressions, we found increased P3 amplitudes for repeated facial expressions compared to novel expressions, suggestive of increased efforts for repeated vs. novel faces. Previous studies indicated that these enhancements to repeated stimuli may be observed when a memory trace is being created (Peykarjou et al., 2016). Consequently, one could hypothesize that representations were built during their repeated presentation. This may in turn suggest that facial expression categories are not yet stable in young children and thus new exemplars of the same emotion category were added to children's memory. Alternatively, behavioral studies suggested that the matching of similar compared to dissimilar facial representation requires highly demanding, effortful controlled information processing (Sonneville et al., 2002; Watling & Damaskinou, 2018). Therefore, it may be that young children needed to activate more neuronal resources for matching repeated expressions (Vlamings et al., 2010). Both of these explanations add to the existing literature of the P3 indicating that this component can be associated with facial expression differentiation (W. Luo et al., 2010). In addition, the differential pattern of repetition for early and late neuronal stages suggest differential top-down and bottom-up processing of facial expressions apparent in young children (Schindler & Bublatzky, 2020).

As another alternative explanation, task demands might have been responsible for increased neuronal activity to repeated compared to novel expressions. Given that we presented a novel facial identity in every trial rather than keeping the identity constant across the whole experiment, it is possible that young children's performance was hampered by the need to process two different facial dimensions (identity and emotion). This explanation might likely also account for the null findings for the N170 which has been associated both with the processing of facial identity (Schweinberger & Neumann, 2016) and the encoding of emotions (Hinojosa et al., 2015). In addition, a recent systematic review indicated that N170 effects were most frequently observed in passive viewing designs, indicating that concurrent task-dependent resources might have competed with resources of emotional decoding at this processing stage (Schindler & Bublatzky, 2020). However, we aimed to overcome this task load by increasing the typical face presentation time to ensure individual face discrimination (Peykarjou et al., 2016). Another study also provides evidence that performance in emotional facial expression processing is similar to identity processing in young children (Johnston et al., 2011). However, we cannot exclude the possibility that their representation of Face 1 may have not been comprehensive enough to reduce processing efforts upon Face 2.

As suggested by previous studies, repetition effects might be enhanced by presenting several repetitions of the same face to build a stable stimulus' representation (Campanella et al., 2002; He & Johnson, 2018; Müller et al., 2013). In contrast, participants in our study only saw a repeated face once which might have hampered repetition modulations. Another difference to former research is that we used longer than usual stimulus' presentation times (Campanella et al., 2002; van Strien et al., 2011) to allow for complete encoding of the facial expressions (Peykarjou et al., 2016) given that young children's face memory may not be as refined yet (Brenna et al., 2015). In addition, we employed a short ISI between Face 1 and Face 2 to decrease cognitive load (Mueller et al., 2020). Ultimately, we cannot exclude the possibility that cognitive load may have still been too high for our sample of young children. One also has to take into account that there might be higher heterogeneity in processing strategies as compared to adult samples (Cohen Kadosh et al., 2013). Clearly, further work is required to test these alternative possibilities, as well as to tease apart those task features that are critical for effects of emotion repetition.

Associations between repetition effects and socio-emotional competence measures

None of the correlations between P1 and P3 difference scores and emotion recognition or empathy scores were significant. Some of the previous research work examining preschoolers' facial processing also indicated null findings when linking ERP responses with socio-emotional competencies (e.g., D'Hondt et al., 2017; Vlamings et al., 2010). In addition, studies which detected significant associations, mostly reported significant brain-behavior correlations in children from high-risk environments (Curtis & Cicchetti, 2011) or in clinical samples (e.g., autism spectrum conditions; Dawson et al., 2004) Since our sample consisted of neurotypical children from families with a middle to high socio-economic status, variability of the data might have been too small to find effects. In addition, the study was powered for within-subject ERP effects, not for interindividual differences which - given the current sample - are bound to be rather small and thus not detectable by our correlational analysis. From a developmental perspective, young children only begin to understand other peoples' emotions as well as differences between own and other's emotions (Denham, 2018). Further, empathic skills within this age range are still maturing which might have also hampered effects. In line with previous research, it may also be possible that other socio-emotional competencies such as emotion regulation may be more susceptible to neuronal associations (Dennis et al., 2009). Thus, our null findings of associating the P1 and P3 with socio-emotional competence measures do not necessarily imply that presented ERP effects are not related to facial expression processing. Even if there would be truly no effect, the ERP components might still reflect the processing of emotional expressions; but reflecting processes that are not susceptible to (subclinical) interindividual differences.

Future directions

With our study, we confirmed that the ability to recognize emotions from facial expression differs depending on type of emotion in young children (Durand et al., 2007). To further understand the stability of perceptual boundaries between facial expression categories, future studies could use varying facial expression intensity to capture the threshold at which neuronal modulations by emotion as well as repetition are observable (Gao & Maurer, 2010). In parallel, assessments of arousal for different intensities could be collected to further examine the degree to which young children are aroused by facial expression stimuli and whether arousal levels are distinct between emotions (e.g., between positive or negative valences). This in turn could also add to the ongoing discussion about the discriminatory power of emotion categorization in comparison to a more dimensional approach (e.g., see Posner et al., 2005). Additionally, the ecological validity of the paradigm could be increased with more naturalistic and dynamic instead of static emotional facial expressions (Quadrelli et al., 2019), which would also allow studying the variability and context-dependency of emotions in childhood (V. LoBue & Ogren, 2022). Future research might also vary the number of repetitions or the degree of stimulus' familiarity to disentangle potential effects of face identity and emotion. Some studies also reported that repetition effects are greater for familiar than unfamiliar faces, so it might be useful to examine ERP effects with faces that preschoolers already know prior to the experiment (Henson, 2016). Regarding the relation of socio-emotional competences and ERPs, a broader range of both behavioral measures and variety in facial expressions could be examined to more specifically bridge the gap between neuronal correlates and concrete behavior. Further, it would be interesting to investigate modulations of ERP responses to facial expression regarding individual differences in children's temperamental or personality traits.

Limitations

To inform about limitations of general cognitive abilities or face memory in the developing brain, the paradigm could be tested within a longitudinal framework to look at improvement over time (Watling & Damaskinou, 2018). When comparing different age groups, it would be of special interest to examine whether there are changes in processing throughout the course of the experiment which could give insights about if and how a mental representation of a facial expression category is built (Nordt et al., 2016). Furthermore, one has to note that the number of trials for the emotion x repetition interaction was quite low. Our sample consisted of young children for whom it is challenging to go through very many trial repetitions. The small number of trials might have contributed to decreases signal-to-noise ratio which may in the future be addressed by examining fewer facial expressions with more trials. In addition, we observed slight amplitude modulations for the different experimental conditions starting already at baseline level. These differences may be also linked to decreases in signal-to-noise ratio, but could reflect potentially meaningful differences in emotion processing that should be also addressed in future research. Lastly, our sample consisted predominantly of upper/middle-class families. There is a need of children from low economic backgrounds to replicate findings in higher risk and more diverse samples (Bhavnani et al., 2021).

Conclusions

The current study confirms that basic mechanisms of facial expression processing are already in place in young children. Within the age range targeted here, early perceptual processes seem to be predominantly activated when encoding differences between facial expressions. Paralleling previous behavioral findings, repetition effects were particularly apparent for happy facial expressions in early processing stages. In contrast, in-depth neuronal face processing was dominated by angry facial expressions. Further studies are warranted to determine the stability of facial expression processing throughout different developmental periods.

3.1.5 Supplementary Material

Delayed match-to-sample-task

Table S3.1.1 Results of the general linear mixed model (GLMM) used to test the hypotheses for accuracy rates and the linear mixed model used to test the hypotheses for reaction times (RT) of the delayed match-to-sample-task.

	Accuracy				Reaction time			
Predictors	Odds Ratios	SE	t	p	Estimates	SE	t	p
Emotion (E) vs. Neutral (N)	1.00	0.11	0.03	0.974	0.05	0.05	1.01	0.311
Happy (H) vs. Angry (A)	0.85	0.08	-1.79	0.074	0.09	0.04	2.14	0.032
Repetition	0.99	0.08	-0.07	0.946	-0.02	0.03	-0.55	0.586
E vs. N x Repetition	1.25	0.27	1.05	0.294	-0.20	0.09	-2.18	0.030
H vs. A x Repetition	1.30	0.24	1.38	0.169	-0.11	0.08	-1.31	0.189
Working Memory	0.84	0.13	-1.14	0.255	0.06	0.06	1.00	0.319
Random Effects								
σ^2	3.29				0.71			
τ_{00}	0.03 $_{\text{Stim\_Type}}$				0.01 $_{\text{Stim\_Type}}$			
	0.60 $_{\text{ID}}$				0.10 $_{\text{ID}}$			
ICC	0.16				0.14			
N	28 $_{\text{ID}}$				28 $_{\text{ID}}$			
	72 $_{\text{Stim\_Type}}$				72 $_{\text{Stim\_Type}}$			
Marginal R^2 / Conditional R^2	0.010 / 0.169				0.009 / 0.144			

Note: p-values for the fixed effects calculated using Wald-statistics approximation, uncorrected. Model equations: Response ~ Emotion * Repetition + Working Memory + (1 | ID) + (1 | Stim_Type); RTs_log ~ Emotion * Repetition + Working Memory + (1 | ID) + (1 | Stim_Type). *SE*: standard error; *t*: test statistic coefficient; *p*: p-value; σ^2: within-group variance; $\tau 00$: between-group variance; *ICC*: interclass correlation (ratio of between-cluster variance to total variance); *N*: number of random effects.

Table S3.1.2 Post-hoc comparisons for Reaction times Emotional vs. Neutral x Repetition.

Comparison						
condition		condition	Est.	SE	z-value	p_{FDR}
neutral $_{\text{novel}}$	-	angry $_{\text{novel}}$	0.04	.06	-0.72	.90
neutral $_{\text{novel}}$	-	happy $_{\text{novel}}$	0.18	.06	3.21	.01
neutral $_{\text{repeated}}$	-	angry $_{\text{repeated}}$	-0.06	.06	-1.00	.75
neutral $_{\text{repeated}}$	-	happy $_{\text{repeated}}$	-0.02	.06	-0.43	.98

Note. Est: estimates. *SE*: standard error. p_{FDR}: FDR-corrected p-values.

ERP analyses

Table S3.1.3 Results of the linear mixed models used to test the hypotheses for the facial expression and repetition effects at the P1, N170 and P3 component for Face 2.

	P1 Amplitude				N170 Amplitude				P3 Amplitude			
Predictors	b	SE	t	p	b	SE	t	p	b	SE	t	p
Emotion (E) vs. Neutral (N)	1.29	0.40	-3.20	0.001	-0.08	0.38	-0.22	0.826	-1.05	0.45	-2.22	0.020
Happy (H) vs. Angry (A)	-0.27	0.35	-0.77	0442	0.11	0.33	0.32	0.749	1.10	0.39	2.84	0.004
Repetition	-0.11	0.33	-0.34	0.732	0.07	0.28	0.26	0.798	0.88	0.36	2.46	0.014
E vs. N x Repetition	1.20	0.81	1.49	0.137	0.87	0.77	1.14	0.256	0.73	0.90	0.81	0.420
H vs. A x Repetition	2.75	0.70	3.92	<0.001	1.16	0.66	1.76	0.079	-0.78	0.78	-0.99	0.321
Working Memory	1.05	0.97	1.08	0.278	0.78	0.63	1.24	0.217	0.38	1.23	0.31	0.760
Stimulus' Contrast	0.36	0.21	1.67	0.095	0.04	0.14	0.30	0.761	-0.50	0.23	-2.19	0.029
Random Effects												
σ^2	269.64				222.67				337.94			
τ_{00}	5.99 $_{Stim\_Type}$				0.19 $_{Stim\_Type}$				5.49 $_{Stim\_Type}$			
	26.54 $_{ID}$				10.79 $_{ID}$				43.24 $_{ID}$			
	8.99 $_{Elect\_site}$				1.57 $_{Elect\_site}$				3.46 $_{Elect\_site}$			
ICC	0.13				0.05				0.13			
N	28 $_{ID}$				28 $_{ID}$				28 $_{ID}$			
	72 $_{Stim\_Type}$				72 $_{Stim\_Type}$				72 $_{Stim\_Type}$			
	7 $_{Elect\_site}$				6 $_{Elect\_site}$				7 $_{Elect\_site}$			
Marginal R^2 / Conditional R^2	0.006 / 0.138				0.003 / 0.056				0.002 / 0.136			

Note: p-values for the fixed effects calculated using Wald-statistics approximation, uncorrected. Model equations: mean_ amplitude P1/ mean amplitude N170/ mean amplitude P3 ~ Emotion * Repetition + Working Memory + Stimulus' Contrast + (1 | ID) + (1 | Stim_Type) + (1 | Electrode). *SE*: standard error; *t*: test statistic coefficient; *p*: p-value; σ^2: within-group variance; $\tau 00$: between-group variance; *ICC*: interclass correlation (ratio of between-cluster variance to total variance); *N*: number of random effects.

Table S3.1.4 Post-hoc comparisons of P1 amplitudes for E vs. N contrast (Face 2).

Comparison						
condition		condition	Est.	SE	z-value	p_{FDR}
neutral	-	happy	-0.83	0.35	-2.38	.033
neutral	-	angry	-1.10	0.35	-3.18	.003

Note. Est: estimates. *SE*: standard error. p_{FDR}: FDR-corrected p-value.

Table S3.1.5 Post-hoc comparisons for P1 amplitude E vs. N x Repetition contrast (Face 2).

Comparison						
condition		condition	Est.	SE	z-value	p_{FDR}
happy $_{novel}$	-	angry $_{novel}$	1.64	0.49	3.33	.005
happy $_{novel}$	-	angry $_{repeated}$	0.68	0.50	1.35	.533
angry $_{repeated}$	-	angry $_{novel}$	0.96	0.52	1.86	.246
happy $_{repeated}$	-	angry $_{novel}$	-0.15	0.53	-0.27	.993
happy $_{repeated}$	-	happy $_{novel}$	-1.79	0.52	-3.44	.003
happy $_{repeated}$	-	angry $_{repeated}$	-1.11	0.50	-2.23	.115

Note. Est: estimates. *SE*: standard error. p_{FDR}: FDR-corrected p-value.

Table S3.1.6 Post-hoc comparisons of P3 amplitudes for E vs. N contrast (Face 2).

Comparison						
condition		condition	Est.	SE	z-value	p_{FDR}
neutral	-	happy	-0.24	0.39	-0.61	.767
neutral	-	angry	-1.34	0.39	-3.42	.001

Note. Est: estimates. *SE*: standard error. p_{FDR}: FDR-corrected p-value.

Table S3.1.7 Results of the linear mixed models for the P1, N170 and P3 component at Face 1.

	P1 Amplitude				N170 Amplitude				P3 Amplitude			
Predictors	b	SE	t	p	b	SE	t	p	b	SE	t	p
Emotion vs. Neutral	-1.55	0.42	-3.72	$<$0.001	-0.79	0.40	-1.96	0.050	-2.18	0.49	-4.49	$<$0.001
Happy vs. Angry	0.34	0.37	0.93	0.352	1.05	0.36	2.94	0.003	0.96	0.43	2.23	0.026
Stimulus' Contrast	-0.28	0.21	-1.32	0.187	0.11	0.16	0.69	0.490	-0.20	0.26	-0.76	0.445
Working Memory	0.51	0.98	0.52	0.601	0.20	0.61	0.32	0.747	1.18	1.11	1.06	0.289
Random Effects												
σ^2	281.10				238.02				379.72			
τ_{00}	3.50 $_{\text{Stim\_Type}}$				0.63 $_{\text{Stim\_Type}}$				6.47 $_{\text{Stim\_Type}}$			
	26.96 $_{\text{ID}}$				10.20 $_{\text{ID}}$				34.77 $_{\text{ID}}$			
	6.54 $_{\text{Elect\_site}}$				3.52 $_{\text{Elect\_site}}$				4.53 $_{\text{Elect\_site}}$			
ICC	0.12				0.06				0.11			
N	28 $_{\text{ID}}$				28 $_{\text{ID}}$				28 $_{\text{ID}}$			
	72 $_{\text{Stim\_Type}}$				72 $_{\text{Stim\_Type}}$				72 $_{\text{Stim\_Type}}$			
	7 $_{\text{Elect\_site}}$				6 $_{\text{Elect\_site}}$				7 $_{\text{Elect\_site}}$			
Marginal R^2 / Conditional R^2	0.002 / 0.118				0.001 / 0.058				0.005 / 0.112			

Note. p-values for the fixed effects calculated using Wald-statistics approximation, uncorrected. Model equations: mean_ amplitude P1/ mean amplitude N170/ mean amplitude P3 ~ Emotion + Working Memory + Stimulus' Contrast + (1 | ID) + (1 | Stim_Type) + (1 | Electrode). *SE*: standard error; *t*: test statistic coefficient; *p*: p-value; σ^2: within-group variance; $\tau 00$: between-group variance; *ICC*: interclass correlation (ratio of between-cluster variance to total variance); *N*: number of random effects.

Table S3.1.8 Post-hoc comparisons of P1 amplitudes for E vs. N contrast (Face 1).

Comparison						
condition		condition	Est.	SE	z-value	p_{FDR}
neutral	-	happy	-0.91	0.36	-2.52	.023
neutral	-	angry	-1.34	0.36	-3.72	$<$ .001

Note. Est: estimates. *SE*: standard error. p_{FDR}: FDR-corrected p-value.

Table S3.1.9 Post-hoc comparisons of P3 amplitudes for E vs. N contrast (Face 1).

Comparison						
condition		condition	Est.	SE	z-value	p_{FDR}
neutral	-	happy	-1.12	0.42	-2.66	.015
neutral	-	angry	-2.12	0.42	-5.04	$<$ .001

Note. Est: estimates. *SE*: standard error. p_{FDR}: FDR-corrected p-value.

Emotion recognition and empathy measures

Emotion matching task (EMT)

Table S3.1.10 Results of the general linear mixed model and linear mixed model used to test the hypotheses for the accuracy rates and reaction times of the emotion matching task (EMT).

	Accuracy				Reaction time			
Predictors	Odds Ratios	SE	t	p	Estimates	SE	t	p
Emotional vs. Neutral	1.10	0.22	0.50	0.619	0.11	0.04	2.58	0.010
Happy vs. Angry	1.39	0.24	1.92	0.055	0.05	0.04	1.31	0.190
Working Memory	1.25	0.26	1.10	0.272	0.05	0.06	0.78	0.436
Random Effects								
σ^2	3.29				0.24			
τ_{00}	1.08 $_{Stim\_Type}$				0.00 $_{Stim\_Type}$			
	1.07 $_{ID}$				0.10 $_{ID}$			
ICC	0.40				0.30			
N	28 $_{ID}$				28 $_{ID}$			
	59 $_{Stim\_Type}$				59 $_{Stim\_Type}$			
Marginal R^2 / Conditional R^2	0.013 / 0.403				0.011 / 0.312			

Note. p-values for the fixed effects calculated using Wald-statistics approximation, uncorrected. Model equations: Response ~ Emo_Neu + Hap_Ang + Working Memory + (1 | ID) + (1 | Stim_Type); RT_log ~ Emo_Neu + Hap_Ang + Working Memory + (1 | ID) + (1 |Stim_Type). EMT: Emotion matching task. *SE*: standard error; *t*: test statistic coefficient; *p*: p-value; σ^2: within-group variance; $\tau 00$: between-group variance; *ICC*: interclass correlation (ratio of between-cluster variance to total variance); *N*: number of random effects.

Table S3.1.11 Post-hoc comparisons of reaction times for emotional vs. neutral contrast.

Comparison						
condition		condition	Est.	SE	z-value	p_{FDR}
angry	-	neutral	-.06	.04	-1.6	.18
happy	-	neutral	-.10	.04	-2.9	.01

Note. Est: estimates. *SE*: standard error. p_{FDR}: FDR-corrected p-value.

ERP associations with socio-emotional competence measures

Table S3.1.12 Correlations between the standardized composite EMK 3-6 empathy (EM) score and P1 and P3 amplitude difference scores.

	r	t	p uncorrected
EMK EM composite score	-	-	-
P1 Diff. happy $_{novel}$ – happy $_{repeated}$	-.15 [-.48, .21]	-0.84	.41
P1 Diff. happy $_{novel}$ – angry $_{novel}$	-.05 [-.40, .31]	-0.26	.79
P3 Diff. novel – repeated	-.12 [-.46, .24]	-0.66	.52

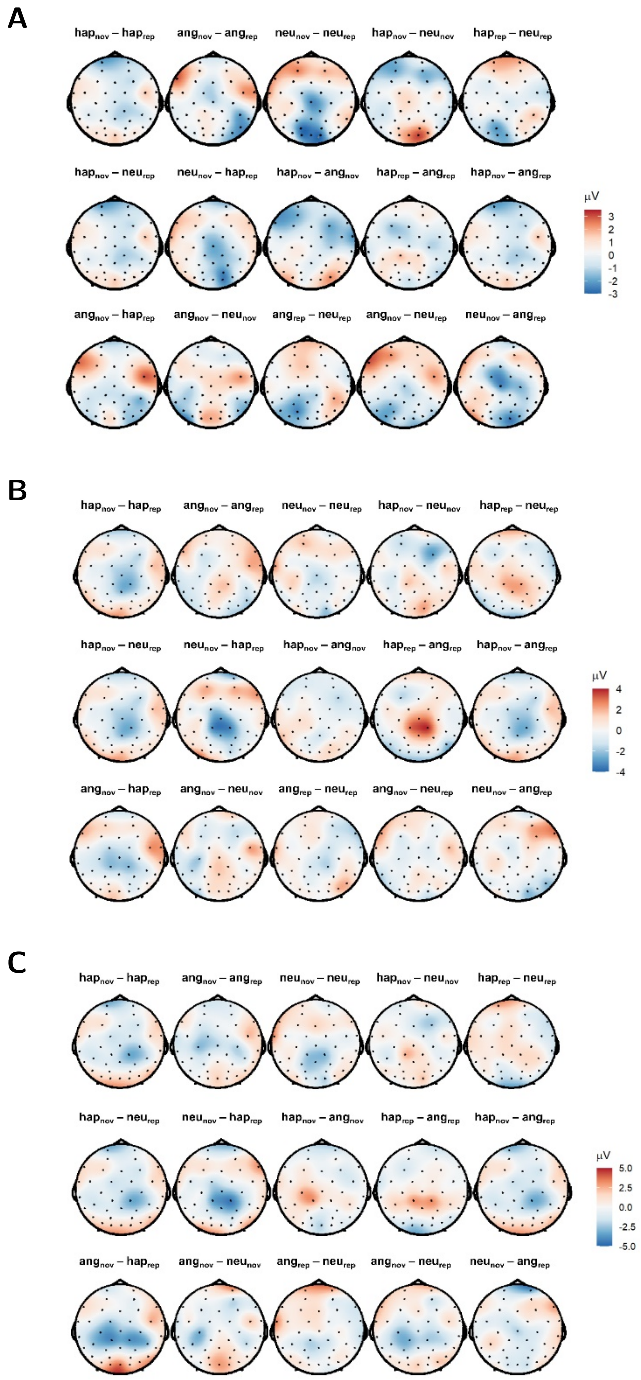
Note. Correlation coefficients were computed with Pearson's correlations. EMK 3-6 EM: Composite score for empathy of the *Inventory to survey of emotional competences for three to six-year-olds.* Values in square brackets indicate the 95% confidence interval for each correlation.

Table S3.1.13 Correlations between the standardized composite EMK 3-6 emotion recognition (ER) score and P1 and P3 amplitude difference scores.

	r	t	p uncorrected
EMK ER composite score	-	-	-
P1 Diff. happy $_{novel}$ – happy $_{repeated}$	.06 [-.41, .30]	-0.34	.74
P1 Diff. happy $_{novel}$ – angry $_{novel}$	.01 [-.36, .35]	-0.04	.97
P3 Diff. novel – repeated	-.07 [-.42, .29]	-0.39	.70

Note. Correlation coefficients were computed with Pearson's correlations. EMK 3-6 EK: Composite score for emotion recognition of the *Inventory to survey of emotional competences for three to six-year-olds.* Values in square brackets indicate the 95% confidence interval for each correlation.

Figure S3.1.1 Topographies of the averaged A) P1 (90-130 ms), B) N170 (180-220 ms), C) P3 (300-500 ms) activity displaying difference topographies (in μV) for the emotion x repetition interaction.



3.2 Neuronal Mechanisms of Preschoolers' Emotion Recognition: Study 2

Enhanced neural sensitivity to brief changes of happy over angry facial expressions in preschoolers: A fast periodic visual stimulation study

Sandra Naumann, Mareike Bayer, Isabel Dziobek

Abstract: Across childhood, emotion perception from facial expressions has traditionally been studied with event-related potentials (ERP). Here, we explored the novel fast periodic visual stimulation (FPVS) EEG approach to provide information about how brief changes in facial expressions are processed implicitly in young children's brains. Employing two FPVS tasks for the first time in preschoolers, we examined brain responses to (1) the discrimination of brief changes in facial expressions at maximum intensity and (2) thresholds for discrimination of gradual increasing facial expression intensities. Within a stream of neutral faces at 6 Hz, happy and angry faces were embedded with a frequency of 1.2 Hz. Additionally, children performed an emotion recognition task (ERT). Data was collected in the context of a training study for socio-emotional competencies with typically developing children (N = 74; 5.1(0.9) years; 34 females). FPVS data was collected post-training, where training was included as a controlling factor. Across FPVS tasks, we detected robust expression change responses, particularly with larger responses for happy vs. angry faces in the maximum-intensity task. ERT results paralleled neuronal findings with faster reaction times and higher accuracy rates for happy vs. angry faces. For gradual increases of emotional intensity, we found linear increases in responses across emotions. The majority of the sample showed a significant expression change at 60 % intensity. With its implicit nature, short duration and robustness of individual responses, our results highlight the potential of FPVS in comparison to classical ERP methods to study neuronal mechanisms of emotion perception in preschool samples.

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3.2.1 Introduction

Recognizing and comprehending the emotions of others lays the groundwork for more complex socio-emotional competencies such as empathy (Trentacosta & Fine, 2010; Zajdel et al., 2013) and prosocial behavior (Brazzelli et al., 2022). Preschool age (3 to 6 years) is a crucial period for the development of emotion recognition, as increased interactions with others provide numerous social learning opportunities (Denham, 2018; Denham et al., 2009). Within this age range, the ability to differentiate emotions seems to be still maturing (Camras & Halberstadt, 2017; Weigelt et al., 2014): While preschoolers recognize others' positive facial expressions with precision comparable to adults (Durand et al., 2007), they are less accurate in recognizing negative facial expressions (Gao & Maurer, 2010).

How facial expression processing unfolds in the brain during this phase of life has previously been examined with electroencephalography (EEG; e.g., Curtis & Cicchetti, 2011; Naumann, Bayer, & Dziobek, 2022). Due to its easy, fast and non-invasive applicability, it is particularly suitable for populations with attentional constraints as well as a high need to move (e.g., infants or young children). Previous research indicated that event-related potentials (ERPs) can be used to map early and late facial expression processing differences in preschoolers (Curtis & Cicchetti, 2011; D'Hondt et al., 2017; Naumann, Bayer, & Dziobek, 2022; Vlamings et al., 2010). The ERP components P1 and N170 were the most commonly reported neuronal responses to face and expressive face stimuli within this age range (Bhavnani et al., 2021). These early, sensory components were associated with the initial and automatic detection of facial features and structural face processing (peaks at 100 ms and 170 ms, Ding et al., 2017; Hinojosa et al., 2015). Higher-order, later ERPs, such as the P3 component were linked to in-depth face processing (typically observed after 300 ms; W. Luo et al., 2010). Though findings are heterogeneous, the majority of studies using passive face viewing paradigms implied that, in comparison to neutral facial expressions, positive and negative facial expressions led to increases in amplitudes of early and late components in preschool-aged children (Curtis & Cicchetti, 2011; Naumann, Bayer, & Dziobek, 2022; Vlamings et al., 2010). As these patterns of results are comparable to studies with adult samples (Schindler & Bublatzky, 2020), they may indicate that basic neuronal mechanisms of facial expression processing are already in place within this age range.

These ERP findings provide first insights into how preschoolers' brains process different facial expressions. However, in everyday situations, facial expressions can briefly and constantly change (e.g., from a more neutral expression to a happy smirk). Thus, for a more comprehensive understanding of facial expression perception, research investigating the ability to detect brief facial expression changes in preschoolers is needed. In addition, the above-mentioned studies used prototypical, exaggerated facial expressions, which may not be typically encountered every day (Schneider et al., 2022). Thus, employing more subtle facial cues could be helpful to delineate the sensitivity to more naturalistic facial expressions (Leleu et al., 2018). Additionally, younger populations have natural constraints in attentional resources, often leading to high loss of trials in EEG setups, e.g. due to movement, of up to 50% (Leppänen et al., 2007). This has a detrimental effect on the signal-to-noise ratio (SNR) and thus on data quality (Luck, 2005). To address these shortcomings, a relatively new approach to quantify the EEG signal, *Fast Periodic Visual Stimulation* (FPVS, Rossion et al., 2015), was recently employed in adult and child samples (Dzhelyova et al., 2017; Leleu et al., 2018; Lochy et al., 2019; van der Donck et al., 2019; Vettori et al., 2019). An FPVS paradigm is designed similarly to a classical ERP oddball paradigm, in which a deviant (expressive) face is presented in a stream of (neutral) faces. Standard and deviant faces are shown at different frequencies (Rossion et al., 2015; e.g., stream of neutral faces at 6 Hz, interleaved with expressive faces at 1.2 Hz). If the brain detects these differences between stimuli, its response is measurable at the same frequencies (base rate for neutral faces; expression change rate for [deviant] expressive faces). Therefore, underlying the FPVS approach is the assumption that periodically presented stimuli elicit synchronization in the brain and thus a response at the same frequency (Adrian & Matthews, 1934) that can be record in an EEG steady-state visual evoked potential (SSVEP; see Norcia et al., 2015 for review). The implicit response to the stimulation sequences constitutes a major advantage over explicit measures (e.g., response times or accuracy rates) as the latter are often biased in developmental samples due to the inability to understand the task, general inhibition, or processing speed problems (Maguire et al., 2014; van der Donck et al., 2019). Robust responses in FPVS data are already visible after brief stimulation periods (e.g., Dzhelyova et al., 2017) and quantifiable at the individual level (Leleu et al., 2018). Furthermore, time windows for mean or peak amplitude analyses in ERP research are often defined post-hoc by the experimenter, which hampers comparability across studies (Luck & Gaspelin, 2017). Within the FPVS approach, frequencies are determined before the experiment, corresponding to the presentation frequencies. Additionally, results of an FPVS task can be quantified in two ways (Dzhelyova et al., 2017; Leleu et al., 2018): information can be obtained from the frequency- and time-domain, which allows the examination of temporal trajectories comparable to ERP quantification procedures.

First studies implementing FPVS to examine brief expression changes in adults show promising results: Dzhelyova and colleagues (2017) presented either upright or inverted streams of neutral faces interleaved with happy, fearful or disgusted facial expressions. Across two experiments, they detected a reliable expression change response for all emotions. Differences between emotions, however, were inconclusive: One observation detectable in both experiments was a larger expression change response for happy faces in comparison to faces bearing an emotion with a negative valence (fear, disgust) in parietal areas (Dzhelyova et al., 2017). In addition, FPVS signals translated into a tri-phasic response in the time domain, which was comparable to an ERP trajectory after presenting facial expressions (e.g., with peaks at the P1, N170, and P3 time windows). A second FPVS study with adults included facial expressions in increasing intensity to investigate which threshold was needed to elicit significant expression change responses (Leleu et al., 2018). All displayed emotions (anger, disgust, happiness, fear, sadness) elicited notable expression change responses. Disgusted faces showed the largest expression change response, whereas sad faces elicited the lowest responses. In addition, frequency power increased with increasing expression intensity, indicating higher brain synchronization with higher intensity. In line with previous research, the authors also detected a tri-phasic response within the time domain. Expanding the study of Dzhelyova and colleagues (2017), they discussed potential mechanisms for each component. The first component (C1) was linked to low-level face encoding (similar to the P1); the second component (C2) to perceptual face encoding (similar to the N170) and the third component (C3) to facilitate more elaborate processing and categorization of emotional facial expressions (similar to the P3).

When brief expression changes of fearful faces was assessed in 8- to 12-year-old boys in an FPVS paradigm, a reliable expression change response was detected (van der Donck et al., 2019). More importantly, boys with autism showed lower responses than boys without autism, also highlighting the potential of FPVS for clinical applications. So far, the use of the FPVS approach for preschool children has been limited to the visual discrimination of faces from objects or individual faces, i.e. the processing of face identities (Lochy et al., 2019; Lochy et al., 2020). Within these studies, a robust and reliable deviant response was detected with larger responses in the right hemisphere (Lochy et al., 2020).

In light of the previous literature, ERP research has provided an important foundation for tracing neuronal mechanisms of facial expression processing in preschoolers. The rather new FPVS method may provide a way to add to this understanding, providing additional information about how brief changes in facial expressions are processed in the brain. First studies with adults and older children show promising results, which need expansion to younger samples. Hence, within our work, we employed the FPVS approach to examine preschoolers' brain responses to brief expression changes. Following previous FPVS procedures (Dzhelyova et al., 2017; Leleu et al., 2018; van der Donck et al., 2019), we employed two tasks (see Figure 3.2.1): The first task tested the discrimination of brief changes of facial expression with expressions at maximum intensity (hereafter 'max-int' task). The second task examined the threshold for the discrimination of facial expressions with gradual increasing expression intensity (hereafter 'grad-int' task). In accordance to previous literature, we also examined time-domain information in addition to the frequency-domain analysis (Dzhelyova et al., 2017; Leleu et al., 2018).

Firstly, we investigated whether preschoolers can pick up brief changes of facial expression reliably, which would be indicated by visible responses to the expression change rate foremost within the max-int task and the right hemisphere (Lochy et al., 2020; Vettori et al., 2019). Secondly, we examined potential processing differences between emotions employing angry and happy faces. In accordance with previous FPVS literature partially detecting larger values for positive vs. negative emotions (Dzhelyova et al., 2017), we hypothesized that happy faces would elicit larger signals than angry faces in both frequency and time analysis within both FPVS tasks. We also based this hypothesis on previous behavioural studies, which showed that happy faces are most readily processed in young children (Durand et al., 2007; Gao & Maurer, 2010) as well previous ERP results (Naumann et al., 2023). Thirdly, we investigated potential threshold differences for increasing emotion intensities within the grad-int task. In line with previous FPVS literature (Leleu et al., 2018), we hypothesized that there is a linear increase in signal with increasing expression intensity in the expression change response as well as a linear decrease in the base response. Besides the two FPVS tasks, we also employed an explicit emotion recognition task (ERT) to measure how well preschoolers are able to distinguish neutral faces from expressive faces at different intensities. Relating to previous behavioural research (Durand et al., 2007; Gao & Maurer, 2010), we hypothesized a processing advantage for happy faces, detectable in higher accuracy rates as well as faster reaction times for happy compared to angry faces.

In a more exploratory fashion, we examined individual expression change response trajectories for each participant (Leleu et al., 2018). We used a qualitative approach to detect potential individual variation as well patterns across the sample. In addition, we also compared modulations in FPVS responses attributable to a digital social-emotional training called *Zirkus Empathico* to previous ERP findings assessing the same sample.

3.2.2 Methods

The FPVS tasks were part of a pre-registered training study (German register for clinical studies: DRKS-ID: DRKS00015789); the study was approved by the local ethics committee. Two digital trainings were contrasted: Zirkus Empathico to foster social-emotional competences in preschoolers and Squirell & Bär, targeting early foreign language acquisition through the interaction with basic English words (see Supplementary Material Description S3.2.1 for detailed information).The training study was pre-registered with a sample size of 74 young children aged 4 to 6 years to provide 80 % power at a two-sided 5% α-level (G*Power; Faul et al., 2007). Results of the training study have been recently published (https://psyarxiv.com/dkxp9/). Within this study, we focused on the neuronal mechanisms of facial expression processing in preschoolers and not the modulation by training. Nevertheless, the factor training was integrated in all analysis to control for its potential effects and to compare to previous ERP findings of the same sample.

Participants

Regarding the FPVS data, we excluded participants due to (a) non-compliance (n = 10, e.g., children became bored or agitated during the fast stimulation sequences and thus closed their eyes), (b) heavy movement (n = 10, e.g., children tried to imitate the perceived expression change, which led to large muscle artifacts), or (c) technical problems (n = 10, e.g., not all event triggers were recorded due to a software error) during data acquisition. In addition, since max-int and grad-int conditions were recorded separately, not all children provided equally sufficient data for both conditions (e.g., heavy movements in one of the conditions), resulting in varying sample sizes for max-int (N = 47) and grad-int (N = 44). The rather high attrition rates (max-int: 36.5%; grad-int: 40.5%) are comparable to previous studies which collected (neuro)physiological data from child samples (e.g., see Dawson et al., 2004: 44.0% or Tottenham et al., 2013: 36.4%).

All participants were of Central European origin. We also assessed children's nonverbal IQ (Coloured Progressive Matrices, CPM; Raven, 2002) and verbal age (Peabody Picture Vocabulary Test, PPVT; Dunn & Dunn, 2007). To describe families' socioeconomic status (SES), we summarized family income, caregiver occupation, and education with the Winkler index (Winkler & Stolzenberg, 1998). Families' SES ranged from medium to high. There were no differences between training and control groups in terms of their participant characteristics, which is why we provide concatenated information across groups separated for each FPVS experiment (see Table 3.2.1 for demographic and screening information).

Table 3.2.1 Participant sociodemographic information for max-int and grad-int.

Characteristics		max-int (N = 47)	grad-int (N = 44)
Sex	Female / Male	21 / 26	22 / 22
Age	Years *M (SD)*	5.3 (0.9)	5.3 (0.9)
SES (Winkler Index)	Low *n* (%)	2 (4)	1 (2)
	Medium *n* (%)	13 (28)	12 (27)
	High *n* (%)	32 (68)	31 (71)
Verbal age	PPVT percentiles *M (SD)*	64.4 (27.3)	65.0 (27.2)
Nonverbal IQ	CPM score *M (SD)*	15.1 (4.0)	15.3 (4.1)

Note. SES = socioeconomic status (Winkler Index; Winkler & Stolzenberg, 1998) PPVT = Peabody Picture Vocabulary Test, CPM = Coloured Progressive Matrices.

FPVS tasks

As shown in Figure 3.2.1, we used two FPVS tasks: The max-int task tested the discrimination of brief changes of facial expression with expressions at maximum intensity. The grad-int task examined the threshold for the discrimination of facial expressions with gradual increasing expression intensities. Both tasks were administered using Presentation® (Version 17.2, Neurobehavioral Systems, Inc., Berkeley, CA, www.neurobs.com).

Stimuli

For max-int and grad-int, face stimuli consisted of happy, angry, and neutral facial expressions of two males and two females from the Radboud Faces Database (Langner et al., 2010). All stimuli were in full-front view, grey scaled, adjusted to mean luminance and trimmed to the same oval shape to exclude hair and non-facial contours (height: 150 pixels, width: 110 pixels). All faces were presented on a grey background (RGB = 100, 100, 100) using a 15'' monitor (display resolution: 1024 x 767) with a viewing distance of 70 cm (visual angle: 3.27°). For the grad-int experiment, we created face morphs by combining the neutral with the expressive face increasing parametrically in five intensity steps from 20% to 100% expression intensity (Morpheus Photo Morpher, Morpheus Software, 2014).

Stimulation sequences

The max- and grad-int task followed the same FPVS procedure (e.g., Leleu et al., 2018; van der Donck et al., 2019): Each sequence was preceded by a fixation cross displayed for 1000 ms. Subsequently, using a sine wave stimulation, a stream of neutral faces (N) was presented at a base frequency of $f = 6$ Hz. At every fifth position an expressive face of the same individual (E) was displayed corresponding to a frequency of $f/5 = 1.2$ Hz (exemplary stimulation sequence: N

N N N E N; see Figure 3.2.1). To avoid low-level visual cue contamination, stimulus size varied randomly between 90% and 110% (Dzhelyova & Rossion, 2014).

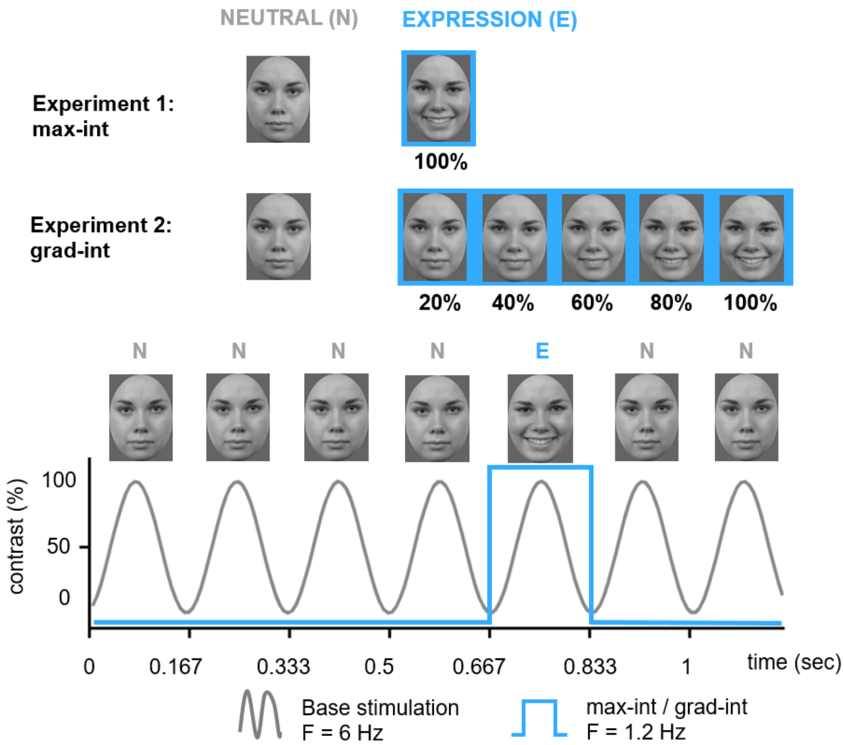


Figure 3.2.1 Fast periodic visual stimulation (FPVS) paradigms used in 2 separate tasks (max-int and grad-int).

In the max-int task, participants observed a neutral face as base stimulus and a happy or angry expression (in separate blocks) at maximum intensity as deviant stimulus. Each emotion condition was presented twice, once with a male and a female identity, summing up to four stimulation sequences in two blocks. Each stimulation sequence had a duration of 40s, resulting in a total length of 160s of stimulation for max-int.

In the grad-int task, happy and angry expressions were shown in five different emotion intensity steps increasing from 20% to 100% in 20 percentage point steps (i.e., 20%, 40%, 60%, 80%, and 100%; Leleu et al., 2018). As for max-int, each emotion category block was shown twice with two male and female identities. Each of the five intensity steps was displayed for 20s, first for the male and then female, summing up to 20 stimulation sequences in 10 blocks with a total duration of 400s. To ensure participant's attention within the grad-int task, we displayed a cartoon monkey face after every intensity step. Participants had to press a button whenever they saw the monkey face. Two practice trials preceded the grad-int task to familiarize children with the procedure.

Emotion Recognition Task (ERT)

After the completion of the max-int and grad-int tasks, participants completed an explicit emotion recognition task (ERT). They saw a face morph stimulus from the grad-int task on screen for a maximum of 3 seconds and had to indicate via a button press whether the face was neutral or yielding an emotion. Children had two buttons available for either neutral or expressive face decisions. Happy and angry faces were presented together with their associated neutral faces in separate blocks (60 trials each, 50 expressive trials [10 trials per intensity], 10 neutral trials). Button order was randomized across participants; reaction times (RT) and accuracy rates were collected.

EEG acquisition and analysis

We collected continuous EEG with the QRefa Acquisition Software (Version 1.0 beta; MPI-CBS, Leipzig, Germany) from 46 Ag/AgCl electrodes (EasyCap GmbH, Germany). EEG data were sampled at 500 Hz (anti-aliasing low-pass filter of 135 Hz) and online-referenced to CZ (ground electrode at Fp1). Electrode impedances were kept below 10 kΩ; electro-oculograms were registered with electrodes at the outer canthi of both eyes and at the orbital ridge of the right eye.

We carried out further offline pre-processing in MATLAB R2016b using EEGlab (Delorme & Makeig, 2004). Data was high-pass filtered at 0.01 Hz and low-pass filtered at 100 Hz (IIR Butterworth filter, 4^{th} order). To improve blink detection using independent component analysis (ICA; runica algorithm), we interpolated artifact-ridden or noisy channels (average channels across participants: max-int: $M = 1.5$; $SD = 0.9$; grad-int: $M = 1.2$; $SD = 0.9$). Within the ICA, components related to blink or saccade activity were removed for each participant (components on average max-int: $M = 3.51$; $SD = 1.32$; grad-int: $M = 4.18$; $SD = 1.43$). The data was re-referenced to average reference.

Frequency-domain analysis

Each epoch was cropped to start at the onset of the first expressive face (max-int: epoch length 40s [47 cycles]; grad-int: 20 s [24 cycles]). Data was then averaged for the different emotions and tasks for each participant. Subsequently, a fast Fourier transform (FFT) was applied to every epoch with a high frequency resolution of 1/40 s = 0.0125 Hz for max-int and 1/20s = 0.05 Hz for grad-int.

We extracted individual base and expression change responses (in µV) for each participant, condition, and electrode for further statistical analysis. Only frequencies corresponding to the frequency of the base rate or the expressive face and its harmonics were considered (Harmonics are integer multiplies of a given frequency i.e., for base response: 1 $f = 6$ Hz, 2 $f = 12$ Hz, 3 $f = 18$ Hz, etc.; for expression change response: 1 $f = 1.2$ Hz, 2 $f = 2.4$ Hz, 3 $f = 3.6$ Hz, etc.). To determine which of the responses carried meaningful signals, i.e., were significantly different from noise, we first determined, on group-level data, the range of harmonics to consider for further analyses. Following previous FPVS procedures (Dzhelyova et al., 2017; Leleu et al., 2018), we applied a *Z*-score transformation: The FFT data was first averaged across all participants and conditions for each electrode. The amplitudes at each harmonic associated with the base and expression change rate were extracted. The respective harmonic amplitudes at one frequency bin (x) were then transformed into *Z*-scores with the following formula: Z = (x - mean noise amplitude) / (standard deviation of the noise). For each frequency bin, the noise was estimated from the respective surrounding 20 frequency bins with 10 bins on each side, excluding the immediately neighboring and the two most extreme values. For each experiment, we determined *Z*-scores > 1.64 (or $p < .05$, one tailed).

Based on this criterion, for the max-int task we quantified significant average expression change responses by summing 5 harmonics: harmonics 1 (1.2 Hz) to 5 (7.2 Hz), excluding the harmonics corresponding to the base stimulation frequency (6 Hz). The base response was quantified as the sum of the response at the base rate (6 Hz) and 2 consecutive harmonics (12 Hz and 18 Hz).

As in previous studies employing the grad-int task (Leleu et al., 2018), the expression-change (1.2 Hz) response was expected to be nearly absent at 20% of expression intensity and to increase with increasing intensity steps. Thus, in accordance with previous studies, we deviated from the Z-score criterion and quantified expression change responses as the sum of 14 harmonics (Dzhelyova et al., 2017; Leleu et al., 2018), i.e. 1 (1.2 Hz) to 14 (16.8 Hz), excluding 6 Hz and 12 Hz for the grad-int experiment. The base response was quantified as the sum of the response at the base rate (6 Hz) and 3 consecutive harmonics (12 Hz, 18 Hz and 24 Hz).

We determined our regions of interest in accordance with previous studies (Lochy et al., 2019; Vettori et al., 2019), confirmed by the greatest Z-scores and visual inspection of the topographical maps of both groups. For both experiments, the analysis of the base response and expression change response for the left cluster was comprised of PO3, PO7, P7, PO9 in left occipito-temporal area; the right cluster of PO4, PO8, P8, PO10 in the right occipito-temporal and the medial cluster of O1, O2, Oz in the medial occipital area (see Figure 3.2.2).

Two measures were used to describe responses in the frequency domain (Dzhelyova et al., 2017): baseline-corrected amplitudes (BCAs) and signal-to-noise ratios (SNRs). BCA values were calculated by applying a baseline-correction to the FFT amplitude values. This was done by subtracting the mean amplitude of the surrounding noise at each frequency bin, using the same noise definition as above. As a final step, BCA values for significant harmonics (determined as described above) were summed to the final base and expression change responses. Summed BCA values were calculated on an individual level for each condition and ROI electrode. SNR values were computed for each participant and condition by dividing the FFT amplitude values at a given frequency bin by the mean amplitude of the estimated noise (same noise definition as above). SNRs were only used for visualization purposes and to describe the strength of the signal in relation to the noise.

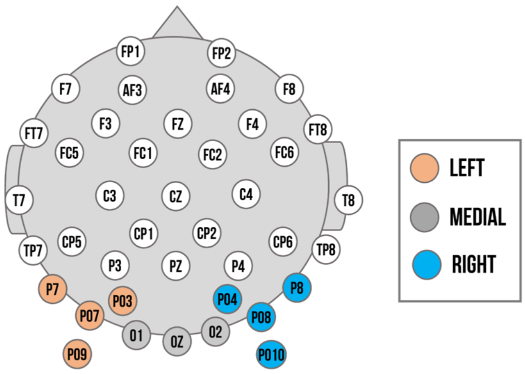


Figure 3.2.2 Electrode setup. Left cluster (electrodes: PO3, PO7, P7, PO9) in orange, medial cluster (electrodes: O1, O2, Oz) in grey and right cluster (electrodes: PO4, PO8, P8, PO10) in blue.

In accordance with previous FPVS approaches (Leleu et al., 2018), we provide additional analyses including a physical dissimilarity index (PDI), which helps to examine whether the significant amplitude increase of the expression-change response as a function of intensity was not solely elicited by increasing physical changes between neutral and expressive faces. The PDI was obtained for each emotion with five linear steps for the increase of expression intensity. Afterwards, summed BCA were normalized for each participant, emotion and intensity by dividing BCA values by the corresponding PDIs (find detailed calculation description in Leleu et al., 2018). These additional calculations were carried out for the expression change response of the grad-int task.

Time-domain analysis

Time-domain analysis was performed to visualize the shape of the periodic changes time-locked to the oddball stimulus, and to estimate the speed and time course of facial expression change. We used a 30 Hz filter as well a FFT notch filter to remove frequency information of the base frequency and its harmonics (Dzhelyova et al., 2017). By filtering out the base response and its harmonics from the EEG data, the signal provides direct expression change specific activities in the time-domain. Data were segmented from -167 ms before stimulus onset to 667 ms post-stimulus onset and baseline-corrected using the mean activity during the 167 ms of the pre-stimulus presentation. For max-int, 90 trials per condition were available; for grad-int, analyses contained 44 trials per intensity step. Segments containing artifacts were removed based on a semi-automated artifact rejection of voltage (exceeding $\pm$ 100 µV) and visual inspection of each trial. No differences between number of trials per facial expression were detected for max-int ($t(92) = -0.7$, $p = .5$; happy: $M = 76.2$; $SD = 10.3$; angry: $M = 74.7$; $SD = 11.2$) or grad-int ($t(86) = 0.3$, $p = .8$; happy: $M = 35.9$; $SD = 4.0$; angry: $M = 36.1$; $SD = 4.3$) after artifact rejection.

Regions of interest for the ERP components and time windows were based on previous research (Lochy et al., 2019; Vettori et al., 2019) and inspection of the ERP topographies averaged across all conditions and participants. For max-int and grad-int tasks, they matched with ROIs selected for the frequency domain analysis (left cluster: PO3, PO7, P7, PO9; right cluster: PO4, PO8, P8, PO10; medial cluster: O1, O2, Oz). In line with previous FPVS research (Leleu et al., 2018), a triphasic response reflecting the discrimination of an emotional expression from a neutral face was identified until approximately 500 ms after expression-change onset (see Figure 3C and 4D). The three components (hereafter C1, C2, C3; respectively positive, negative and positive) sequentially peaked at 176, 256 and 376 ms post expression-change (time-windows: C1: 120-200 ms, C2: 220–300 ms, C3: 350–450 ms; comparable to Leleu et al., 2018). Peaks for each component were quantified as mean amplitude in a time window of 20 ms around the peak. During visual inspection of ERP topographies averaged across all conditions and participants, we did not detect the triphasic response pattern within the medial cluster in the grad-int task. Thus, we only included data of the left and right cluster in the final analysis.

Statistical analysis

Statistical analyses were performed using R-Studio (R Core Team, 2019). For all analyses, we conducted linear mixed model analyses using the packages lme4 (Bates et al., 2015) and sjstats (Lüdecke, 2021). For the analysis of the frequency domain in max-int task, we examined baseline-corrected amplitudes with *emotion* (happy vs. angry expressions) and *ROI* (left vs. right vs. medial) as within-subject factors and *group* (Zirkus Empathico vs. controls) as between-subject factor. *Participant* was included as random intercept in the model. Models for the time domain analysis which included mean amplitudes as dependent variable were identical. We calculated them separately for C1, C2 and C3. For the grad-int task, we included *intensity* (20%, 40%, 60%, 80%, 100%) as additional within-subject factor in both frequency and time domain analysis. We analyzed whether the BCA signal increased in response to the increase in expression intensity and which trend would best describe this increase (e.g., linear, cubic or quadratic trend). Regarding the within-subject factor ROI, we included the left and right cluster for the time domain analysis.

For the models of the RTs and accuracy rates of the ERT, we used the within-subject factors emotion (happy vs. angry expressions) and intensity (20%, 40%, 60%, 80%, 100%) as well as the between-subject factor group (Zirkus Empathico vs. controls). Parallel to the other models, participant was included as random intercept.

Post-hoc t-tests were performed on the fitted model using the emmeans package (Lenth, 2019) with Tukey-corrected p-values used to compare means. We used partial eta squared (η_p^2) to quantify the size of effects (η_p^2; small effect: $\eta_p^2 = .01$, medium effect: $\eta_p^2 = .06$, large effect: $\eta_p^2 = .14$; Keppel, 1991).

3.2.3 Results

Max-int: Dynamics of change for expression discrimination at maximal intensity

Frequency domain: Base response and expression change response

As shown in the left panel of Figure 3.2.3A, a clear base response was visible for the base rate. The 6 Hz response as well as the response of its harmonics were characterized by a medial occipital topography peaking at channel O1 (F = 6 Hz: 1.01 µV, SNR = 5.63; 2F = 12 Hz: 0.59 µV, SNR = 5.77; 3F = 18 Hz: 0.19 µV, SNR = 3.24; Figure 3.2.3A middle panel). Statistical analysis showed a significant main effect of emotion ($F(2,225) = 6.10$, $p = .01$, $\eta_p^2 = .03$; Figure 3.2.3A right panel), with happy faces eliciting a larger base response than angry faces. None of the other comparisons revealed significant results (see Table 3.2.2).

As shown in the left panel of Figure 3.2.3B, a clear expression change response was visible. The highest SNR was detected at the fourth harmonic characterized by a right-sided occipital topography peaking at P8 (F4 = 4.8 Hz: 1.19 µV, SNR = 1.75; Figure 3.2.3B middle panel). SNR values for the 1.2 Hz response and corresponding harmonics were numerically larger for happy vs. angry faces. This finding is in line with our hypothesis as well as in accordance with BCA results, where we detected a significant effect of emotion ($F(1,225) = 52.79$, $p < .001$, $\eta_p^2 = .18$; Figure 3.2.3B right panel), indicating larger BCA values for happy vs. angry faces. Additionally, there was a main effect of ROI ($F(2,225) = 4.17$, $p = .02$, $\eta_p^2 = .03$), indicating larger BCA values for the right as compared to the medial cluster ($p = .02$). None of the other comparisons revealed significant results (see Table 3.2.2).

Table 3.2.2 Max-int task frequency domain analysis: Base and expression change response.

	Base response				Expression change response			
	df	*F*	*p*	η_p^2	df	*F*	*p*	η_p^2
Group	45	0.06	.81	< .001	45	0.83	.37	.003
Emotion	**225**	**6.09**	**.01**	**.026**	**225**	**52.79**	**< .001**	**.177**
ROI	225	1.32	.27	.011	**225**	**4.17**	**.02**	**.033**
Group x Emotion	225	0.34	.56	.001	225	0.03	.87	< .001
Group x ROI	225	0.14	.87	.001	225	3.12	.05	.025
Emotion x ROI	225	0.72	.49	.006	225	0.15	.86	.001
Group x Emotion x ROI	225	0.40	.67	.003	225	0.01	.99	< .001

Time-domain: Amplitude analysis of event-related potentials

For C1, we detected a significant group x ROI interaction ($F(2, 77801) = 3.86$, $p = .02$, $\eta_p^2 < .001$). Compared to controls, participants of the Zirkus Empathico group showed larger amplitudes in the right cluster ($p = 04$). For C2, we found a significant emotion main effect ($F(1, 77769) = 43.47$, $p < .001$, $\eta_p^2 = .001$), with happy faces eliciting a more negative amplitude than angry faces (see Figure 3.2.3C). In addition, analyses revealed a significant ROI main effect ($F(2, 778001) = 8.80$, $p < .001$, $\eta_p^2 < .001$). Amplitudes were largest in the right cluster compared to left ($p < .001$) or medial ($p = .02$) clusters. Regarding C3, we also detected significant main effects of emotion ($F(1, 77845) = 54.03$, $p < .001$, $\eta_p^2 = .001$) and ROI ($F(2, 77801) = 15.47$, $p < .001$, $\eta_p^2 < .001$). Happy faces elicited larger amplitudes than angry faces; amplitudes were lowest in the medial cluster compared to left ($p < .001$) and right ($p < .001$) clusters. In addition, we found a group x ROI interaction (F(1, 77801) = 3.18, $p = .04$,

$\eta_p^2 < .001$), which was further qualified by an Emotion x Group x ROI interaction ($F(2, 77801) = 3.33$, $p = .04$, $\eta_p^2 < .001$). Post-hoc tests indicated enhanced amplitudes for happy faces in the left cluster for the Zirkus Empathico group as compared to controls ($p = .02$; complete statistical information in Table 3.2.3).

Table 3.2.3 Max-int task: Time domain analysis.

	Component 1				Component 2				Component 3			
	df	*F*	*p*	η_p^2	df	*F*	*p*	η_p^2	df	*F*	*p*	η_p^2
Group	45	0.53	.47	< .001	45	0.54	.47	< .001	45	1.21	.28	< .001
Emotion	77815	2.38	.12	< .001	**77769**	**43.48**	**< .001**	**.001**	**77845**	**54.03**	**< .001**	**.001**
ROI	77801	1.57	.21	< .001	**77801**	**8.80**	**< .001**	**< .001**	**77800**	**15.47**	**< .001**	**< .001**
Group x Emotion	77815	2.00	.16	< .001	77769	2.81	.09	< .001	77845	1.30	.25	< .001
Group x ROI	**77801**	**3.86**	**.02**	**< .001**	77801	0.53	.59	< .001	**77800**	**3.18**	**.04**	**< .001**
Emotion x ROI	77801	1.94	.14	< .001	77801	2.84	.05	< .001	77800	0.44	.64	< .001
Group x Emotion x ROI	77801	0.64	.53	< .001	77801	2.63	.07	< .001	**77800**	**3.32**	**.04**	**< .001**

Summary: max-int frequency and time domain findings

We detected larger BCA values for both base and expression change response as well C2 and C3 amplitudes for happy vs. angry faces. In both frequency and time domain, a dominance of the right hemisphere in processing expression change was observed. Regarding group effects, we detected that at C3 (350-450 ms; associated with emotion categorization) participants of the Zirkus Empathico group compared controls showed larger values for happy faces in the left cluster.

Grad-int: Dynamics of change for expression discrimination modulated by increasing intensities

Frequency domain: Base response and expression change response

As shown in the left panel of Figure 3.2.4B, we detected a significant intensity main effect for the base response ($F(4,1218) = 2.74$, $p = .03$, $\eta_p^2 = .01$). Contrary to our expectations, the modulation of BCA values by intensity followed a cubic trend ($p = .01$). In addition, we found a significant ROI main effect ($F(2,1218) = 7.94$, $p < .01$, $\eta_p^2 = .01$; Figure 3.2.4C left panel), with larger BCA values for the right vs. left ($p = .01$) or medial ($p < .01$) cluster. We also detected a significant group x ROI interaction ($F(2,1218) = 3.47$, $p = .03$, $\eta_p^2 = .01$), however, none of the post-hoc tests were significant (all $p > .05$). All statistical comparisons are reported in Table 3.2.4.

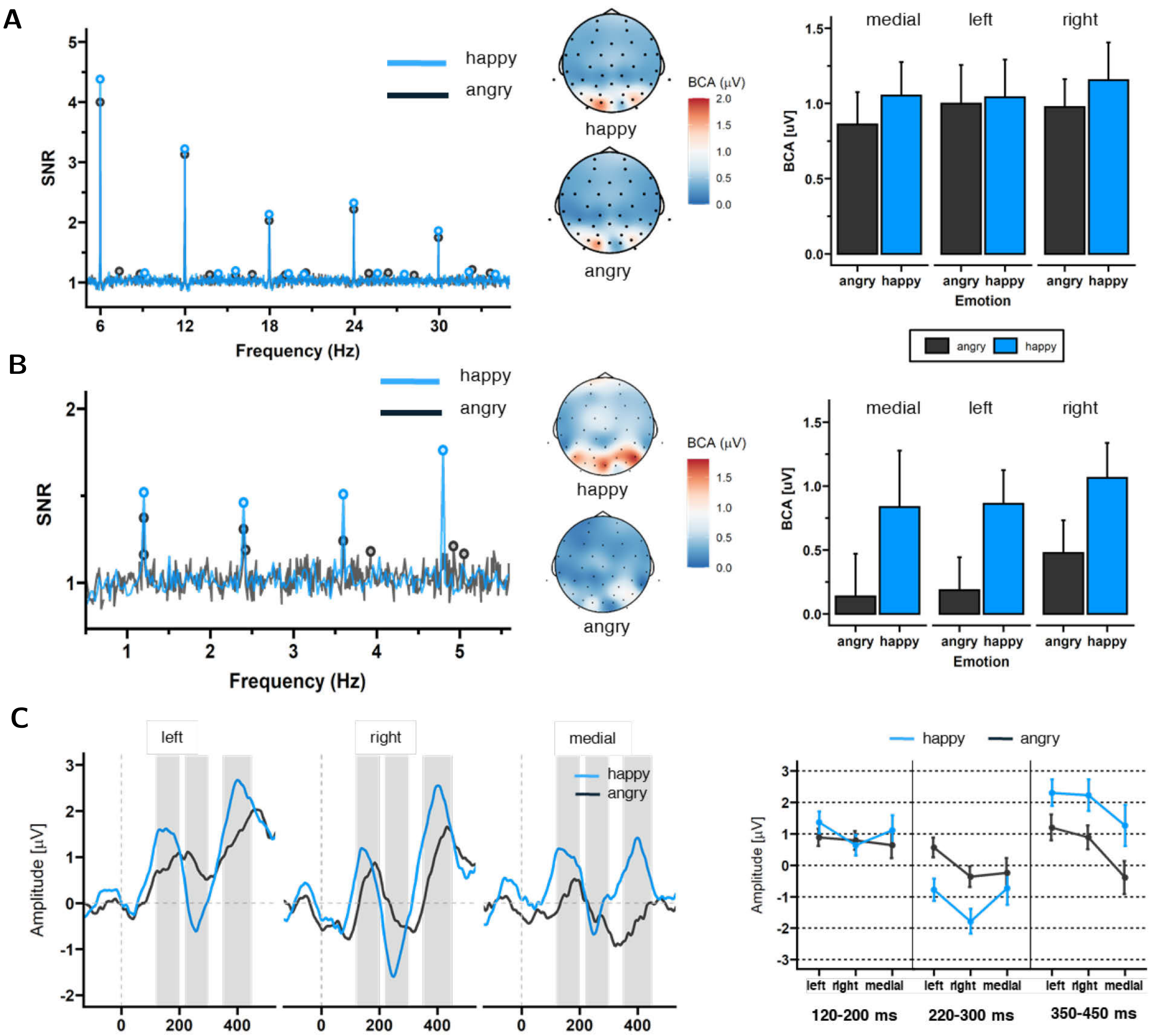


Figure 3.2.3 Visualization of max-int task frequency and time domain results. All results are separated for the different facial expressions (light blue = happy, dark blue = angry) and averaged across ROI channels (left cluster: PO3, PO7, P7, PO9; right cluster: PO4, PO8, P8, PO10; medial cluster: O1, O2, Oz). (A) Base response: [left panel] SNR spectra. [middle panel] Scalp topographies (in µV). [right panel] Bar graphs displaying BCA values. Error bars indicate standard errors (SE). (B) Expression change response: [left panel] SNR spectra. [middle panel] Scalp topographies (in µV). [right panel] Bar graphs displaying BCA values. Error bars indicate standard errors (SE). (C) ERP waveforms and mean amplitudes: [left panel] Waveforms for C1, C2 and C3. Shadowed areas indicate the time windows used to identify participants' individual peaks and mean amplitudes. [right panel] Mean C1, C2, and C3 amplitudes and standard deviations separated for each time window.

Regarding the expression change response, we did not detect identifiable SNR responses at 20% intensity (Figure 3.2.4A right panel). In contrast, at 100% intensity, we found clearly identifiable SNR responses in particular for happy faces. Statistical analysis showed a significant intensity main effect (F(4,1218) = 5.29, $p < .01$, $\eta_p^2 = .02$), with larger BCA values for 100% vs. 20% intensity ($p < .001$; Figure 3.2.4B right panel).

Table 3.2.4 Grad-int task frequency domain analysis: Base and expression change response.

	Base response				Expression change response			
	df	F	p	η_p^2	df	F	p	η_p^2
Emotion	1218	1.83	.18	< .001	1218	0.04	.85	< .001
Intensity	**1218**	**2.74**	**.03**	**.01**	**1218**	**5.29**	**< .01**	**.02**
Group	43	1.96	.17	< .001	43	0.05	.82	< .001
ROI	**1218**	**7.94**	**> .01**	**.01**	**1218**	**6.74**	**<.01**	**.01**
Emotion x Intensity	1218	0.50	.73	< .001	**1218**	**2.58**	**.04**	**.01**
Emotion x Group	1218	2.31	.13	< .001	1218	1.29	.26	< .001
Intensity x Group	1218	0.86	.49	< .001	1218	2.28	.06	.01
Emotion x ROI	1218	0.43	.65	< .001	1218	1.43	.24	< .001
Intensity x ROI	1218	0.28	.87	< .001	1218	1.19	.30	.01
Group x ROI	**1218**	**3.47**	**.03**	**.01**	1218	0.37	.69	< .001
Emotion x Intensity x Group	1218	1.27	.28	< .001	1218	1.00	.41	< .001
Emotion x Intensity x ROI	1218	0.44	.90	< .001	1218	1.01	.43	.01
Emotion x Group x ROI	1218	0.11	.89	< .001	1218	0.25	.78	< .001
Intensity x Group x ROI	1218	0.26	.98	< .001	1218	1.38	.20	.01
Emotion x Intensity x Group x ROI	1218	0.25	.98	< .001	1218	0.57	.81	< .001

In line with our hypothesis, the modulation of BCA values by intensity followed a linear trend ($p < .01$): Increasing facial expression intensity elicited a linear enhancement of BCA values. We also detected a significant ROI main effect ($F(2,1218) = 6.74$, $p < .01$, $\eta_p^2 = .01$), with larger BCA values for the right vs. medial cluster (p < .01; Figure 3.2.4C right panel). In addition, there was a significant emotion x intensity interaction ($F(4,1218) = 2.58$, $p = .04$, $\eta_p^2 = .01$). However, within our additional analysis, in which we corrected with PDI values, the emotion x intensity interaction effect did not remain significant ($F(4,1218) = 0.91$, $p = .46$, $\eta_p^2 < .01$; see Supplementary Material Table S3.2.1 for statistical analysis with PDI correction). Thus, in principle, responses for happy and angry were significant, but no difference between emotions was detected.

Time-domain: Amplitude analysis of event-related potentials

For C1, we detected a significant intensity main effect (linear trend: $p < .001$), as well as several interactions (all statistical parameters in Table 3.2.5). As one of them was a four-way interaction of emotion x intensity x group x ROI, we examined left and right clusters separately to simplify analyses. The main effect of intensity was significant in both clusters (left: $F(4,62419) = 5.14$, $p < .01$, $\eta_p^2 < .001$; right: $F(4,62420) = 4.08$, $p < .01$, $\eta_p^2 < .001$). However, only within the left cluster, we found another significant effect, namely an emotion x intensity x group interaction ($F(4,62425) = 3.96$, $p < .01$, $\eta_p^2 < .001$). At 100 % intensity, controls showed larger amplitudes for angry faces compared to the Zirkus Empathico group (all other post-hoc tests: $p > .08$).

Table 3.2.5 Grad-int task: Time domain analysis.

	Component 1				Component 2				Component 3			
	df	F	p	η_p^2	df	F	p	η_p^2	df	F	p	η_p^2
Emotion	124877	3.05	.08	< .001	**124875**	**112.58**	**<.01**	**< .001**	**124869**	**16.56**	**<.01**	**< .001**
Intensity	**124868**	**7.72**	**< .01**	**< .001**	**124866**	**3.81**	**<.01**	**< .001**	**124862**	**42.26**	**<.01**	**< .001**
Group	42	0.20	.66	< .001	42	0.09	.77	< .001	42	0.03	.87	< .001
ROI	124846	0.06	.80	< .001	124846	1,24	.26	< .001	**124846**	**6.93**	**.01**	**< .001**
Emotion x Intensity	124873	1.05	.38	< .001	**124872**	**6.16**	**<.01**	**< .001**	**124867**	**3.66**	**.01**	**< .001**
Emotion x Group	124877	0.79	.37	< .001	**124875**	**11.90**	**<.01**	**< .001**	124869	0.92	.34	< .001
Intensity x Group	**124868**	**3.01**	**.02**	**< .001**	**124866**	**5.48**	**<.01**	**< .001**	124862	2.13	.07	< .001
Emotion x ROI	124846	0.19	.66	< .001	124846	0.01	.92	< .001	**124846**	**5.31**	**.02**	**< .001**
Intensity x ROI	124846	1.33	.25	< .001	124846	2.21	.06	< .001	124846	1.02	.39	< .001
Group x ROI	**124846**	**10.51**	**<.01**	**< .001**	124846	2.62	.11	< .001	**124846**	**11.57**	**<.01**	**< .001**
Emotion x Intensity x Group	**124873**	**4.33**	**.01**	**< .001**	124872	1.03	.39	< .001	**124867**	**5.56**	**<.01**	**< .001**
Emotion x Intensity x ROI	124846	0.71	.58	< .001	124846	1.22	.30	< .001	124846	1.32	.26	< .001
Emotion x Group x ROI	124846	0.50	.48	< .001	124846	2.06	.15	< .001	**124846**	**4.18**	**.04**	**< .001**
Intensity x Group x ROI	124846	1.41	.23	< .001	**124846**	**2.43**	**.04**	**< .001**	124846	1.94	.10	< .001
Emo. x Int. x Gr. x ROI	**124846**	**2.99**	**.02**	**< .001**	124846	1.31	.26	< .001	124846	1.22	.30	< .001

For C2 (see Figure 3.2.4D and Table 3.2.5), we detected significant main effects of emotion and intensity (linear trend: $p < .01$), which where qualified by an emotion x intensity interaction. Except for 20% intensity ($p = .09$), happy faces elicited larger amplitudes than angry faces across intensities (all $p < .001$). The significant intensity x group interaction did not contain any significant post-hoc test results (all $p < .05$). We found a significant emotion x group interaction, with both groups showing larger values for happy vs. angry faces. Lastly, we detected an intensity x group x ROI interaction. Compared to controls, the Zirkus Empathico group showed enhanced amplitudes in the right cluster at 60% intensity ($p < .001$).

For C3, we found significant main effects of emotion (happy > angry), intensity (linear trend: $p < .001$) as well as ROI (right cluster > left cluster). As shown in Table 5, several two-way interactions were significant, which were qualified by two three-way interactions (emotion x intensity x group and emotion x group x ROI). For the emotion x intensity x group interaction, post-hoc tests revealed that amplitudes for angry faces at 100% intensity were larger for controls vs. Zirkus Empathico participants ($p = .03$). The other three-way interaction did not reveal any significant post-hoc results (all $p > .10$).

Summary: grad-int frequency and time domain findings

Regarding the frequency domain, we detected a cubic modulation by intensity for the base response, and a linear increase of signal for the expression change response. No modulation by emotion was detected. Similar to the max-int task, a dominance of the right hemisphere for processing expression change was observed. With regard to the time domain, C2 (perceptual coding) and C3 (emotion categorization) indicated an increase in signal with increasing intensity as well as larger amplitudes for happy vs. angry faces. In addition, we found topographical as well as intensity processing differences when comparing the Zirkus Empathico group and controls.

Exploratory analysis: Individual neuronal trajectories for facial expression detection

We determined each participant's neuronal thresholds for significant base and expression change responses. Given that after PDI correction intensity did not interact with emotion (although both happy and angry faces did elicit significant responses), individual responses were averaged across emotions and their significance was estimated using the same criterion as for the group-level analysis. Lastly, we clustered participants by their group allocation into the Zirkus Empathico (Figure 3.2.5A), and control group (Figure 3.2.5B). Regarding the base response, the cubic trend detected in the statistical analysis was visible. When visually inspecting the data, we observed signal increases up until 60% intensity which were then followed by decreases or fluctuations (e.g., significant response for 80%, but not 100% intensity) in signal in both groups (Zirkus Empathico: 46% of participants; Controls: 32% of participants).

For the expression change response, we found large inter-individual differences with a general trend of increasing z-scores with increasing expression intensity. We found significant responses at 20% intensity for 59% of the Zirkus Empathico group and 55% of controls. From 80 % to 100 % intensity, 59% of participants in both groups showed significant responses. Topographically, response patterns were quite variable, with the majority of participants showing their maximum values at 80/100% intensity at electrodes PO4 (23%) and P8 (19%) both located within the right cluster.

Behavioural Measure: Explicit Facial Emotion Processing

As shown in Figure 3.2.6B (upper panel), we detected that emotion (X^2 (1, $N = 44$ $= 104.27$, $p < .001$) had a significant effect on accuracy rates, with happy faces being detected more accurately than angry faces. In addition, there was a significant intensity main effect (X^2 (1, $N = 44 = 104.27$, $p < .001$), indicating that accuracy increased with increasing expression intensity. This relationship was a mixture of linear ($p < .001$) and quadratic components ($p < .001$).

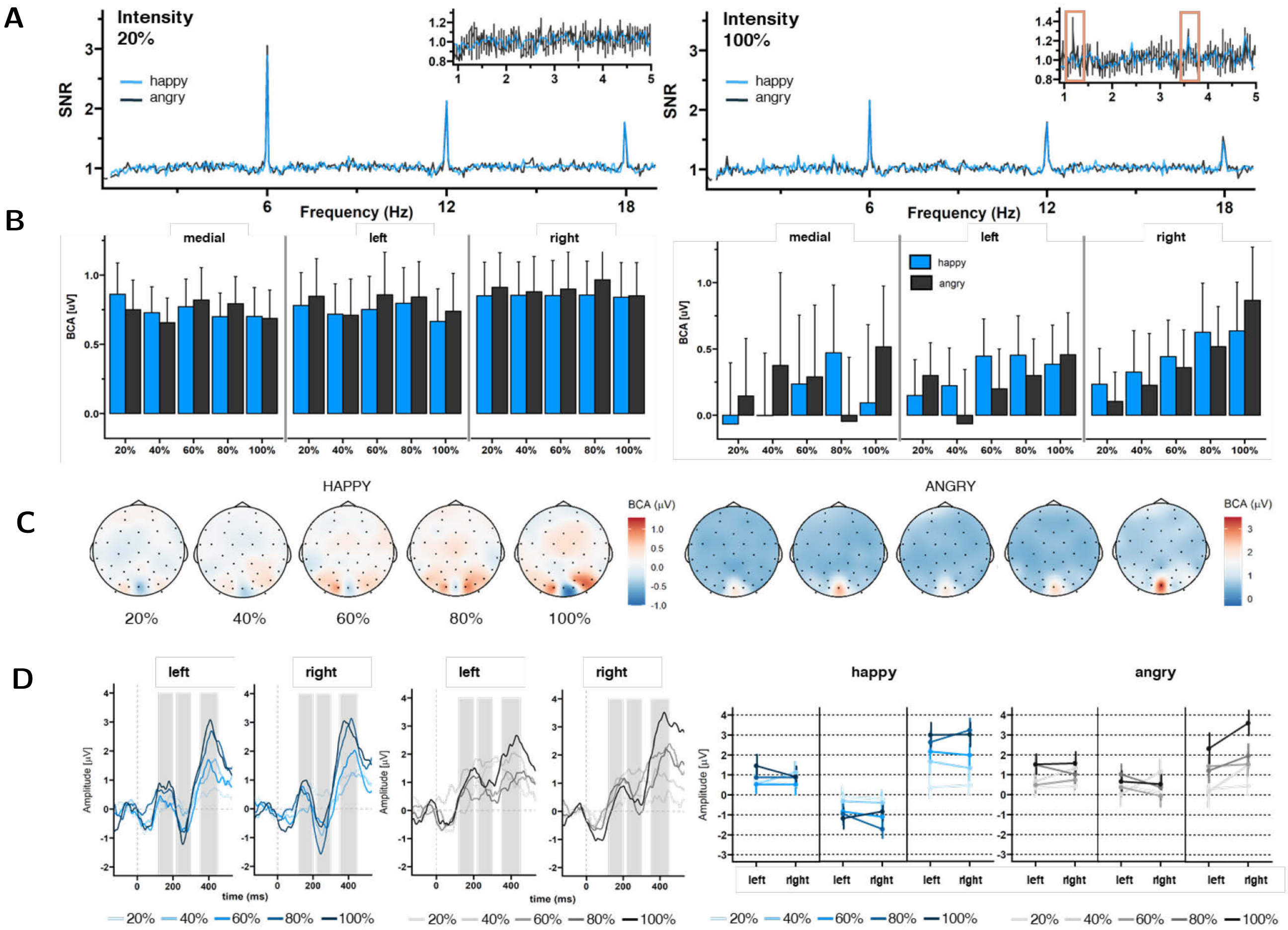
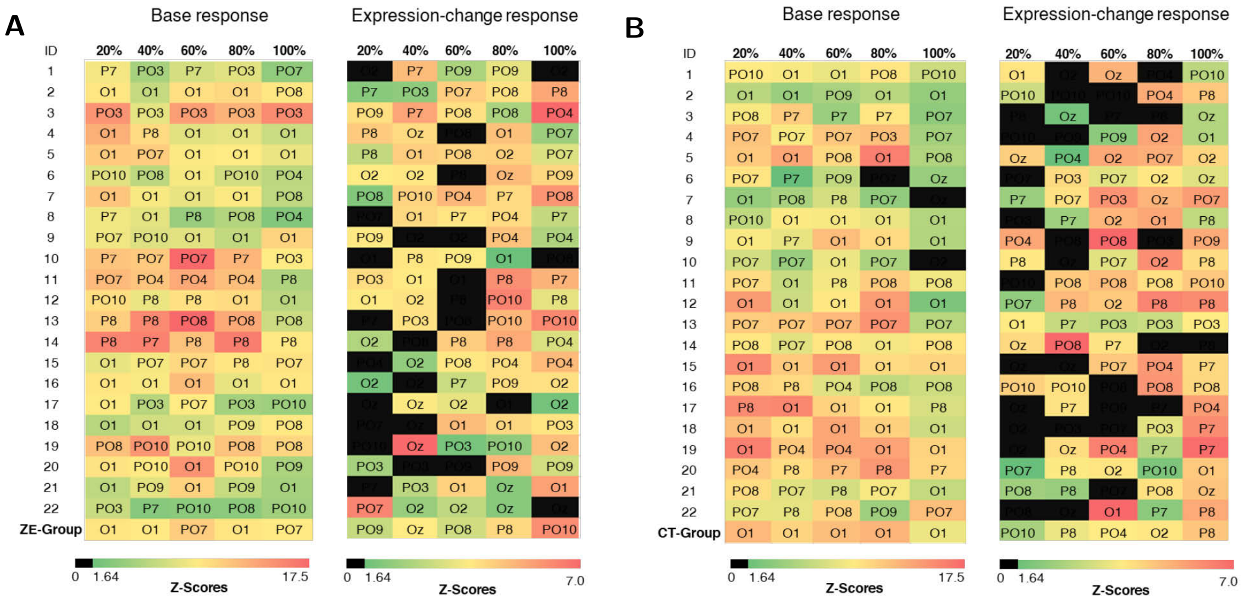


Figure 3.2.4 Visualization of grad-int task frequency and time domain results. All results are separated for the different facial expressions (light blue = happy, dark blue = angry, here also graded by intensity) and averaged across ROI channels (left cluster: PO3, PO7, P7, PO9; right cluster: PO4, PO8, P8, PO10; medial cluster: O1, O2, Oz). (A) SNR spectra for base and expression change response (right upper figures): [left panel] SNR values at 20% intensity. [right panel] SNR values at 100% intensity. (B) Bar graphs displaying BCA values. Error bars indicate standard errors (SE): [left panel] Base response. [right panel] Expression change response. (C) Scalp topographies (in µV): [left panel] Base response. [right panel] Expression change response. (D) waveforms and mean amplitudes: [left panel] Waveforms for C1, C2 and C3. Shadowed areas indicate the time windows used to identify participants' individual peaks and mean amplitudes. [right panel] Mean C1, C2, and C3 amplitudes and standard deviations separated for each time window.

Regarding reaction times visualized in Figure 3.2.6B (lower panel), we detected significant main effects of emotion ($F(1,10) = 38.8$, $p < .001$, $\eta_p^2 = .007$) and intensity ($F(4,10) = 7.95$, $p = .004$, $\eta_p^2 = .005$), which was also qualified by an emotion x intensity interaction ($F(4,10) = 3.97$, $p < .03$, $\eta_p^2 = .003$). Happy faces were detected faster than angry faces at 60% ($p < .001$), 80% ($p < .001$) and 100% ($p < .001$) intensity. The relationship between reaction time and intensity was characterized by a linear trend ($p = .001$)



gure 3.2.5 Color-coded table depicting the strength of the greatest Z-Scores at each intensity step averaged across emotions and its corresponding channel for each individual participant and for the group. (A) Zirkus Empathico group: Base and expression change response. (B) Controls: Base and expression change response.

3.2.4 Discussion

Whereas previous ERP research focused on the neuronal patterns of processing different facial expressions, we investigated an implicit measure of preschoolers' ability to detect brief changes in facial expression (happy and angry expressions), employing the recently introduced FPVS approach. We used two FPVS tasks: Within the first task, we investigated whether preschoolers detect brief changes when emotional facial expressions are presented at maximal intensity. The second task included face morphs gradually increasing in expression intensity to inquire which threshold is needed to detect a facial expression change.

Within the maximum-intensity task, we found reliable expression change responses for happy and angry faces within the frequency and time domain. In addition, we also detected larger expression change rates for happy vs. angry faces. When examining gradual increase of emotion intensity, we detected a linear increase in expression change responses; whereas the trajectory of the base response followed a cubic trend. In line with the maximum-intensity task, differences in expression change responses were apparent within SNRs as well as later components in the time-domain indicating larger expression change responses for happy vs. angry faces. Maximum- and gradual-intensity task findings are paralleled by higher accuracy rates and faster RTs within the emotion recognition task, indicating a processing advantage of happy over angry faces in our preschool sample. The analysis of individual trajectories revealed large inter-individual differences, with the majority of the sample showing significant expression change responses at 60 % intensity.

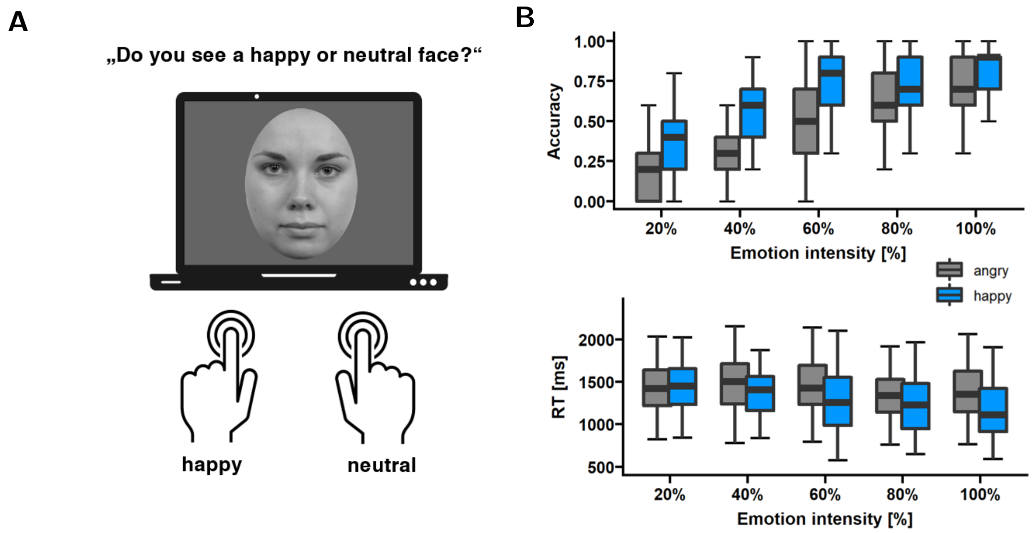


Figure 3.2.6 Emotion recognition task (ERT). (A) Display of task. (B) Accuracy findings [upper panel] Reaction time findings [lower panel].

Our first research question aimed to investigate whether brief changes of expression can be detected in preschoolers' brain response. In line with previous FPVS research (Dzhelyova et al., 2017; Leleu et al., 2018), significant expression change responses within the max-int and grad-int task provide evidence for this hypothesis. The results highlight the value of the FPVS approach to address further developmental questions as it offers an implicit, fast and objective way to measure the ability to detect expression change. Our study focused on typically-developing preschoolers, the promising results, however, also suggest value for clinical groups with emotion processing particularities as for example observed in people on the autism spectrum. Here, FPVS may be helpful for people who are non-verbal or have restrictions in their attention span due to its brevity and implicit nature. In fact, other studies have already successfully used the FPVS approach in the context of individual face (Vettori et al., 2019, 2020) and facial expression discrimination (van der Donck et al., 2019) in autistic 8- to 12- year-old boys.

Regarding our second research aim, we examined differences in expression change for different emotions. In line with our hypothesis, we detected larger responses for happy vs. angry faces, which was particularly visible in the max-int task. This finding is paralleled by previous behavioural research (Durand et al., 2007; Gao & Maurer, 2010) as well as our ERT findings, which indicated a processing advantage of happy faces. In addition, as part of the pre-registered training study, we also conducted a passive face viewing task to measure ERPs, in which we also detected larger activity for happy faces in components P1 and P3 (Naumann et al., 2023). Thus, we would conclude that happy faces are more readily processed than angry faces by preschoolers, adding evidence to the framework of the progressive development of emotions (Camras & Halberstadt, 2017). The slower development of angry or other emotions with a negative valence such as fear or sadness could be explained by the typically lower exposure to these emotions in everyday life of preschoolers (Gao & Maurer, 2010; Leppänen et al., 2007). Furthermore, previous research formulated an initial-negativity hypothesis, assuming that a preliminary bias may exist toward processing emotionally ambiguous faces, such as neutral expressions with a negative valence (Petro et al., 2018; Rollins et al., 2021). Particularly children under the age of nine seem to interpret neutral faces ambiguously (either more positive or negative; Durand et al., 2007). Taken together with the fact that changes in facial expression were presented very briefly (under 200 ms), these factors might have contributed to the lower expression change responses for angry faces.

Unexpectedly, we also detected modulations by emotion within the base response. This finding partly parallels previous FPVS research, indicating that the base response involves more than low-level processes and seems reflective of both low- and high-level processes (Dzhelyova et al., 2017). This pattern could be particularly pronounced in preschoolers, as emotion recognition is still maturing (Camras & Halberstadt, 2017) and early, low-level processes are assumed to play an important role within this age range (Batty & Taylor, 2006).

In this context it seems interesting to discuss how much the responses of the FPVS task are indeed associated with affective as compared to purely perceptual processing. In terms of single facial features, a happy face typically includes a smile, which has been shown to be more salient than any other region of happy and non-happy faces (Calvo & Nummenmaa, 2008), which is also linked to its luminance, contrast and spatial orientation (Borji & Itti, 2013). Hence, being more salient and distinctive may have impacted the modulation of the change response for happy faces. However, since the FPVS approach controls for differences in low-level processing by varying the stimulus size during the presentation (Rossion et al., 2015), this is less likely to confound the results. In addition, we also controlled the physical properties of our stimuli and used the PDI (Leleu et al., 2018) to control for contrast differences. The possibility that expression recognition may have mainly relied on the perceptual analysis of visual features rather than emotional meaning, however, cannot be clearly excluded (Calvo & Nummenmaa, 2016), particularly because of the brief changes of expression. However, one could argue that this highly-controlled decontextualised experimental setting can only be seen as first proxy to real-life behaviour and that, in daily life, faces appear in context where the affective evaluation plays a detrimental role (Calvo & Nummenmaa, 2016).

For the grad-int task, there was no significant difference between emotions, which is in line with previous research using a similar research design for adults (Leleu et al., 2018). Since the stimulation sequence duration was halved compared to the max-int task, one could argue that effects might have been hampered by lower statistical power. In addition, particularly in the conditions with low expression intensities, we barely detected any expression change responses (Leleu et al., 2018). Thus, it is possible that, due to this reduced power, effects were less likely to be detected. However, differences were visible within the time domain analysis of the grad-int-task, displaying larger amplitudes for happy vs. angry faces at C2 and C3 connected to perceptual encoding and emotion categorization (Leleu et al., 2018). This finding can be related to previous ERP research in preschoolers, where modulations by emotion where found for the higher-order P3 component (Naumann, Bayer, & Dziobek, 2022; Naumann et al., 2023).

As our third research aim, we investigated the intensity thresholds for the detection of expression change. Confirming previous research (Leleu et al., 2018), we found an increase in expression change response with increasing expression intensity. When analysing the trend for the base response, however, we did not find an adaption or decrease of signal (Leleu et al., 2018), but a cubic trend. Relating to the individual trajectories of base and expression change responses, we detected that up until 60 % of expression intensity, the neutral face may not be well distinguishable from the expressive face within this age range. This finding is in line with previous behavioural research, which indicated preschoolers needed at least 40 % intensity of emotion to recognize it (Rodger et al., 2018; Rodger et al., 2015). Further, research showed that different age groups use different strategies and neuronal structures for face recognition (Margot J. Taylor et al., 2011), which may also contribute to the observed differential neuronal pattern. In addition, our task slightly diverted from the design of Leleu et al. (2018) in that we added short breaks in between each intensity step. This procedure allowed us to provide children better opportunities to take breaks, which in turn reduced movement artifacts and enhanced compliance. Since we detected the same linear trend for the expression change response as in Leleu et al. (2018), we would see this diversion from the previous protocol as less likely to have modulated the responses. Lastly, the large variability in thresholds could also in part be caused by general factors such as skull thickness and cortical folding (Vettori et al., 2020).

Even though the FPVS tasks were included as part of larger training study comparing the digital training Zirkus Empathico to a control training (Naumann et al., 2023), here we focused on the neuronal mechanisms of facial expression processing in preschoolers and thus implemented the factor training as a control variable. Both in maximum and gradual intensity, some analyses showed differences in neuronal response between the Zirkus Empathico and the control group. However, findings were inconclusive and need to be interpreted carefully: Within the max-int task, we found larger C3 amplitudes for happy faces in the Zirkus Empathico group compared to controls. This finding is comparable to results of the ERP task, which was also recorded as part of the training study (Naumann et al., 2023). Here, we also detected larger P3 amplitudes for happy vs. neutral and angry faces solely within the Zirkus Empathico group. However, these results represent only a fraction of frequency and time domain results, whereas in most of the other analyses, we detected null results for the modulation of training. Thus, we would only derive that differences for such a training may be detectable in later processing stages previously associated with the in-depth analysis of emotion (Naumann, Bayer, & Dziobek, 2022; Schindler & Bublatzky, 2020), which should be further explored in future studies.

Overall, the FPVS results show correspondences with previous findings employing ERPs (Naumann et al., 2023), providing a first piece of evidence that FPVS and ERP show comparable sensitivity to grasp facial expression processing in preschoolers. The FPVS approach, however, seems to show clear advantages compared to the ERP method in terms of its execution speed and robustness even on the individual level. In addition, FPVS data can be analysed in the frequency and time domain, allowing for a better comprehension of synchronization and temporal brain processes.

Regarding limitations, we examined data from a controlled, narrow-aged preschool sample which allowed us to learn more about the developmental processes of this specific age range. However, we cannot derive conclusions for other age groups as development unfolds rapidly within the first years of life (Denham, 2018; Denham et al., 2009). In addition, our sample consisted of families of European origin which had a middle to high socio-economic status, which further limits generalizability. In the future, the inclusion of several methods, which quantify the EEG signal such as ERPs or other frequency band analyses to disentangle neuronal similarities as well as differences mappable with the different methods, may be desirable. FPVS could also be employed cross-sectionally from young childhood to early adulthood to understand how this marker evolves across development. Particularly analyses of individual thresholds for detecting facial expressions could be of value to elaborate which emotion intensity is needed to be reliably detected by the brain. As the FPVS approach due to its speed and implicit nature, offers ways to overcome the limited attention span or non-verbality of participants, it could be expanded to clinical groups with these restrictions who show difficulties in emotion processing (e.g., depression, social anxiety). Within our research, we found a first indication that expression change responses differ with regard to the emotional valence of the faces. Thus, it would be of interest as well to integrate more basic and complex emotions (Calvo & Nummenmaa, 2016) to detect whether they are distinct FPVS patterns for each emotion. Furthermore, to complement this neuronal measure, more behavioural aspects of emotion knowledge or broader socio-emotional competence could be included to understand the strength of association between this neuronal marker and observable behaviour.

Addressing emotion perception with FPVS in preschoolers for the first time, we detected a reliable index of expression change with enhanced processing for happy compared to angry faces. The findings highlight the potential of the FPVS approach to address further developmental questions as it offers an opportunity to measure the ability to detect expression change implicitly, fast, and objectively.

3.2.5 Supplementary Material

Description S3.2.1: Description of training study

Study overview

The study protocol was pre-registered at the German register for clinical studies (DRKS-ID: DRKS00015789). It included a training group which received the socio-emotional touchscreen application Zirkus Empathico (Kirst et al., 2022; Kirst et al., 2015) and an active control group which interacted with the language learning application Squirell and Bär (the Good Evil GmbH). Eligible participants were randomly allocated to the Zirkus Empathico or control group. Baseline socio-emotional competence (targeting empathy, emotion recognition, prosocial behavior) was examined with child assessments and parent ratings prior to training assignment at the study center. For the first measurement, no EEG data was collected. Each family then received a tablet-PC with the assigned touchscreen application to practice at home. Training lasted six weeks, with a weekly engagement of minimum 60 minutes. After six weeks of training at home, parent ratings and child assessments were repeated at the study center by an evaluator who was blind to group assignment. Furthermore, children participated in an EEG measurement. Within the EEG assessment, the maximum-intensity (max-int) and gradual intensity (grad-int) fast periodic visual stimulation (FPVS) task were administered.

Description of training and control touchscreen applications

Zirkus Empathico targets awareness and differentiation of own and others' emotions, empathy, and prosocial behaviors through interactions with naturalistic video sequences of facial expressions and social situations (Kirst et al., 2022; Kirst et al., 2015).The touchscreen application consists of 4 modules and an emotion library. In the first module, the child gets to know the virtual emotion manikin for the first time. The manikin constitutes a central element of the training to support the child in expressing perceived emotions on a two-dimensional scale indicating arousal and valence levels. Firstly, the child can specify its inner emotional state regarding a specific context (emotion-inducing video clip; see Figure S3.2.1). In a second step, the child describes its inner state by choosing an emotion label. Within the second module, the child is asked to identify emotion labels for facial expressions of adult and child protagonists (emotions: happy, sad, angry, anxious, and surprised). The third module requires the child to identify a specific emotion-eliciting context of another person. The child chooses the correct emotion label from 3 options. Within the last module, the child is presented with a third person's emotional expression embedded in an emotion-triggering context. Afterward, the child can decide how to react to the other person (e.g., go and talk to this person), fostering empathy and prosocial actions. Lastly, the library contains explanations of the emotion manikin and the six emotion cards with definitions and explanations of the basic emotional states targeted.

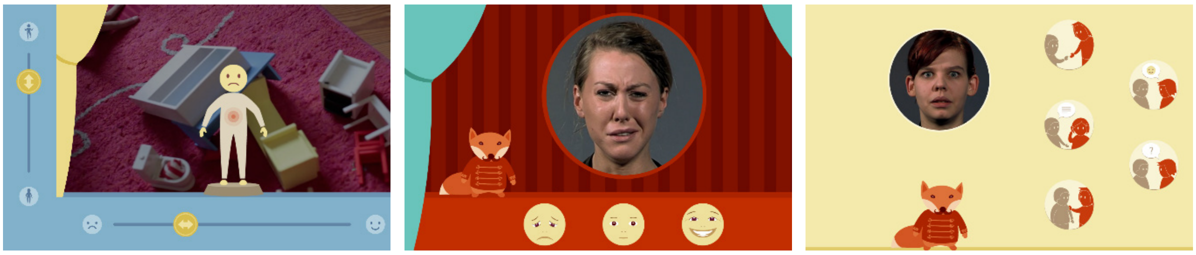


Figure S3.2.1 Training elements of Zirkus Empathico. Left: Module 1 - Understanding own emotions with the virtual manikin. Middle: Module 2 – Detecting and understanding others' emotions . Right: Module 4 – Learning how to react to others' emotions.

As control training, we employed the touchscreen application Squirell & Bär (the Good Evil GmbH), which fosters early foreign language acquisition through the interaction with basic English words and phrases. The child follows a story about a squirrel and a bear who are given the task of saving the bees from extinction. The children learn basic words (e.g. names of animals, food, etc.) as well as first ways to start a conversation (e.g. introduce themselves, ask for directions).

Additional Analysis: Grad-int task expression change with PDI correction

Table S3.2.1 Grad-int task frequency domain analysis: Expression change response corrected with a physical dissimilarity index (PDI).

	Expression change response			
	df	*F*	*p*	η_p^2
Emotion	1218	0.44	.51	< .001
Intensity	1218	2.28	.06	.01
Group	65	0.16	.69	< .01
ROI	1218	2.41	.09	<.01
Emotion x Intensity	1218	0.91	.46	<.01
Emotion x Group	1218	0.16	.69	< .01
Intensity x Group	1218	0.81	.52	<.01
Emotion x ROI	1218	1.62	.20	< .01
Intensity x ROI	1218	0.91	.51	.01
Group x ROI	1218	0.53	.59	< .01
Emotion x Intensity x Group	1218	0.22	.92	< .01
Emotion x Intensity x ROI	1218	1.15	.32	.01
Emotion x Group x ROI	1218	0.25	.48	< .01
Intensity x Group x ROI	1218	2.76	<.01	.02
Emotion x Intensity x Group x ROI	1218	0.45	.89	< .01

3.3 Trainability of Behavioral and Neuronal Correlates of Socio-Emotional Competence: Study 3

A randomized controlled trial on the digital socio-emotional competence training Zirkus Empathico for preschoolers

Sandra Naumann, Mareike Bayer, Simone Kirst, Elke van der Meer, Isabel Dziobek

Abstract: In this randomized controlled trial (RCT), the digital socio-emotional competence training Zirkus Empathico was tested in 74 Central European children (5.1(0.9) years; 34 females) within a longitudinal design (three time points: T1 = pre-training; T2 = immediately following 6-week training, T3 = 3-month follow-up). The preregistered primary outcome was empathy, secondary outcomes included emotion recognition, prosocial behavior and behavioral problem reduction; furthermore, children's neuronal sensitivity to facial expressions quantified with event-related potentials. Compared to controls (N = 38), Zirkus Empathico participants (N = 36) showed increases in empathy (d = 0.28 [-0.17, 0.76]), emotion recognition (d = 0.57 [0.01, 1.06]), prosocial behavior (d = 0.51 [0.05, 0.99]) and reduced behavioral problems (d = 0.54 [0.08, 1.03]). They also showed larger P3 amplitudes to happy vs. angry and neutral facial expressions post-training. Thus, Zirkus Empathico may be a promising digital training for social competence in preschoolers.

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3.3.1 Introduction

Preschool years represent an important period for the development of socio-emotional competence (SEC), which is assumed to be a conglomerate of social and emotional skills that contribute to a child's ability to both adapt to social situations and appropriately assert own needs and interests over others (Holodynski & Rüth, 2021). One of the most central facets of SEC is empathy, a multidimensional construct, which comprises cognitive and affective facets as separate, but interrelated components (Dziobek et al., 2008). Cognitive empathy refers to understanding others' emotions through perspective taking (Frith & Singer, 2008). Emotional resonance may arise from cognitive comprehension and bottom-up processes related to emotion generation and understanding (Decety, 2011), which may eventually trigger feelings of empathic concern manifest in cognitive awareness of own and others' emotional experiences (M. R. Klein et al., 2018) as well as facial and vocal expressions of prosocial actions (Davidov et al., 2013).

As further SEC component, recognizing others' emotions (e.g., through facial expressions) constitutes the primary means of emotional communication for young children (Beauchamp & Anderson, 2010). Emotion recognition includes the awareness that an emotion has been expressed (typically through relevant facial cues, e.g., raised eyebrow, smile), and the labeling of expressions (Castro et al., 2016). Preschoolers reliably express and detect a variety of emotions (Denham, 2018). While positive facial expressions of others are recognized with almost adult-like precision (Durand et al., 2007), preschoolers are less accurate for negative facial expressions (Gao & Maurer, 2010). Emotion recognition is associated positively with empathic concern (Israelashvili et al., 2020). Further, empathy is thought to rely on overlapping neuronal circuits that are activated when processing own emotions (Bird & Viding, 2014; Oliver et al., 2018) and functional awareness of own emotions represents leverage to empathic understanding Bird et al., 2010.

Empathy and emotion recognition correspond significantly with prosocial behavior, which also belongs to the SEC conglomerate (Castro et al., 2016; Farina & Belacchi, 2022; Grueneisen & Warneken, 2022; Salerni & Caprin, 2022; Song, 2022; Trentacosta & Fine, 2010; Yin & Wang, 2022). Prosocial behavior constitutes positive interactions with other people, including behavior that has a positive impact on social relations such as helping, sharing, cooperating, and comforting (Beauchamp & Anderson, 2010; Salerni & Caprin, 2022; Yin & Wang, 2022). Children's prosociality develops from being mostly sympathy-based to becoming more behaviorally varied, selective, and strategic as well as more motivationally and cognitively complex (Grueneisen & Warneken, 2022; Kenward & Dahl, 2011). Empathic concern is linked to prosocial behaviors (Klimecki & Singer, 2013). In later stages of childhood, prosocial behavior develops in relation to emotion recognition and maturating empathy (Blewitt et al., 2018).

Preschool age constitutes a significant time for the initial onset of mental health problems, which often accompany and impact individuals throughout their lives (Fryers & Brugha, 2013; Girard & Okolikj, 2023). The most common mental health presentations in childhood include emotional (e.g., anxiety disorder: childhood prevalence 5.2%; Barican et al., 2022; Steinsbekk et al., 2022 and behavioural difficulties (e.g., attention-deficit/hyperactivity disorder: childhood prevalence 3.7 %; Barican et al., 2022; Tobarra - Sanchez et al., 2022. Preschool prevention and intervention programs often involve the strengthening of SEC (Zarra-Nezhad et al., 2023) as it serves as an important resilience factor against psychological distress (Alwaely et al., 2021; Colomeischi et al., 2022; Romppanen et al., 2021). Children who are socially and emotionally competent have the skills and knowledge needed to build secure interpersonal relationships, regulate their emotions, cope with challenges, and better adjust to preschool (Adela et al., 2011; Beauchamp & Anderson, 2010; Beelman, 2019). In the long run, functional SEC also fosters primary school readiness (Slot et al., 2020), and subsequent academic success (Denham, 2018).

Prevention programs targeting preschoolers Finlon et al., 2015; Koglin & Petermann, 2011 may thus be beneficial to foster SEC development to circumvent manifestations of problematic to pathologic behavior (Wadepohl et al., 2011). In the last decades, the development of SEC training programs for preschool classrooms has made significant progress (Beelman, 2019). Meta-analytic evidence suggests small to moderate effects for classroom-based programs regarding the improvements of different facets of SEC (L. Luo et al., 2022; Murano et al., 2020). More specifically, studies examining German classroom-based trainings (Wiedebusch & Petermann, 2011) detected improvements in emotion recognition and empathy (Wadepohl et al., 2011) as well as prosocial behavior (Koglin & Petermann, 2011; Lösel et al., 2006; Schick & Cierpka, 2006).

Despite promising evidence, it is difficult to individualize and tailor classroom-based programs to the requirements of each child (Mondi et al., 2021). Further, the introduction of large-scale classroom-based programs requires substantial financial resources and infrastructure as well as training of the teaching staff, which complicates a sustainable implementation (Adela et al., 2011; Mondi et al., 2021). In addition, the events of the COVID-19 pandemic entailing for example the immense disruptions in childcare and long-term social distancing, amplified the importance of families' homes as learning environments (Lehrl et al., 2021). During the pandemic, digital teaching and training were among the only viable options given the face-to-face restrictions during this time.

Thus, to overcome shortages in the provision of previous classroom-based programs as well hurdles for socio-emotional learning in restricted contexts (e.g., within a pandemic), it might be fruitful to enhance the implementation of digital SEC trainings in home-based settings (Hollis et al., 2020). Digital trainings can offer relatively naturalistic social learning environments, for example, by integrating animations or video sequences of facial expressions or social interactions (Dziobek, 2012; Rosenblau et al., 2020). They may also enhance the motivation to learn new skills through persuasive design elements and gamified elements (e.g., engaging the reward system Whyte et al., 2015).

While a steep increase in digital interventions targeting mental health in children has been noted over the last years (Hollis et al., 2017), only few studies on the impact of digital SEC trainings are available (Griffith et al., 2020). They mainly target impairments in socio-emotional skills in children with neurodevelopmental conditions such as autism (Song, 2022). For example, the touchscreen application "Zirkus Empathico" has been developed for children with an autism diagnosis and a developmental level between five and ten years (Kirst et al., 2015; Zoerner et al., 2016). Based on principles of autism-specific behavior therapy (e.g., prompting, reinforcement learning; Bernard-Opitz, 2009) and neurobiological models of empathy (Bird & Viding, 2014), the application initially focuses on the awareness and differentiation of own emotional states and facial emotion recognition, before teaching to infer others' emotions from emotion-eliciting contexts. Lastly, the concept of emotional resonance and appropriate prosocial actions expressing empathic concern towards others' emotions within various contexts are conveyed.

A randomized controlled trial (RCT) testing the effectiveness of Zirkus Empathico in 82 five- to ten-year-old children with autism found moderate effects on empathy and emotion recognition in the training compared to the active control group after six weeks of caregiver-guided intervention (training duration: 100 minutes per week; Kirst et al., 2022). While improvements were not present anymore during the three-month follow-up assessment, more stable effects were reported for children's awareness of their own emotions, emotion regulation, and prosocial behavior (Kirst et al., 2022). Due to its simplified language and age-appropriate visualized content, the Zirkus Empathico training might be equally suitable for the needs of preschoolers without formal diagnosis. Since it targets the training of SEC, which still lacks systematic implementation throughout the (pre-) schooling contexts (Wu & Kim, 2019), it could, if proven effective, add tremendous value as educational tool.

Therefore, within our present study, we aimed to extend the purpose of the Zirkus Empathico training and thus assess the effect of this six-week digital SEC training on typically developing preschoolers between 4 and 6 years. Since studies examining the effectiveness of digital trainings to foster preschoolers' SEC development are scarce and do not consider children's home learning environment, we aim to inform and extend the research on digital tools within this area. In order to match the study outcomes to the intervention targets of Zirkus Empathico, empathy (comprising cognitive and affective facets) was defined as the primary outcome. It was hypothesized that a six-week training with Zirkus Empathico would result in greater improvements in empathy in the training group compared to active controls engaging in a digital foreign language acquisition training. To further quantify effects of Zirkus Empathico on a broader range of outcome measures, changes in emotion recognition and prosocial behaviors were assessed as secondary outcomes.

Finally, since previous digital intervention studies have paid minimal attention to neurobiological systems in their evaluation of treatment efficacy, the study additionally examined training-induced changes in event-related potentials (ERPs), underlying the processing of facial expressions. The complementation of behavioral findings with brain measures in the context of the evaluation of treatment efficacy may allow tapping into the development, potential maladaptive processes and resilience in fuller complexity (Cicchetti & Gunnar, 2008). Indeed, as one of the first, Wu and Kim (2019) presented promising evidence in 3-5-year-old preschoolers by assessing the touchscreen application Empathy World with behavioral measures and ERPs. Post-training, the authors found significant increases in attention to others' feelings as well as higher empathic concern which was indexed by modulation of the P2 component (Wu & Kim, 2019).

The current study focused on neuronal correlates of emotion recognition, particularly from facial expressions, as it represents one of the basic building blocks for emotion perception (Halberstadt et al., 2001; LoBue et al., 2019), a key element for empathy and prosocial behavior (Beauchamp & Anderson, 2010; Castro et al., 2016). Modulations by facial expressions have been observed in early and late ERP components which can be classified into several stages of facial emotion perception Schindler & Bublatzky, 2020. As young children seem to process the discrimination of emotions at early stages Batty & Taylor, 2006, the P1 and N170 as early ERP components were the most commonly reported neuronal responses to face and expressive face stimuli for preschool samples Bhavnani et al., 2021. Both ERPs were previously associated with initial sensory and automatic detection of facial expressions in children and adults (Ding et al., 2017; Hinojosa et al., 2015). In addition, we analyzed the P3 component, which is sensitive to the processing of facial expressions in children (Anokhin et al., 2010; Naumann, Bayer, & Dziobek, 2022) and was previously associated with their motivational saliency (Hajcak et al., 2010). The few studies with preschool samples showed that, in comparison to neutral facial expressions, positive and negative facial expressions led to increases in amplitudes of these early and late components in preschoolers (Curtis & Cicchetti, 2011; Vlamings et al., 2010). Studies investigating the link between ERP components and various facets of SEC yield mixed results: P1 amplitudes to fearful and sad faces were correlated positively with a behavioral measure of emotion regulation in preschoolers (Dennis et al., 2009). In adolescence, an inverse correlation between early and late ERPs with cognitive empathy abilities was reported (Mella et al., 2012). Another study including school-age children found that higher social cognition values were associated with a lower P1 amplitude (Hileman et al., 2011). In contrast, other studies did not detect significant correlations, particularly for preschool samples regarding measures of affective empathy and P1 or N170 amplitudes (D'Hondt et al., 2017) or measures of empathy and emotion recognition with P1 or P3 amplitudes (Naumann, Bayer, & Dziobek, 2022).

We hypothesized that after the training, P1 and N170 amplitudes would be larger for the Zirkus Empathico group as compared to controls, indicative of attentional resources dedicated to facial expression processing. Similarly, we expected larger P3 amplitudes for later neuronal processing suggesting greater emotional receptiveness within the Zirkus Empathico group when compared to controls. In additional explorative analyses, possible long-term implications were examined as well as whether parent ratings and child SEC assessments were positively related to ERP amplitudes in response to facial expressions (Dennis et al., 2009).

3.3.2 Methods

Participants

The study protocol was pre-registered at the German register for clinical studies (DRKS-ID: DRKS00015789) and approved by the ethics committee of the Department of Psychology at Humboldt-Universität zu Berlin. The study was conducted in accordance with the Declaration of Helsinki. We recruited families by website postings, newspapers, and postal acquisition. They were compensated with € 24 for study participation. The trial lasted from October 2018 to July 2020. Due to the COVID-19 pandemic, it was interrupted from March to May 2020.

Sample size calculation within the pre-registration was based on a previous meta-analysis reporting a small effect size $d = 0.47$ [0.08, 0.86] (Grynszpan et al., 2014) when examining the effect of technology-based training in children on the autism spectrum (which represented the best estimate at time of pre-registration). Assuming a 20% attrition rate (Wadepohl et al., 2011), we included a total sample of 74 intention-to-treat (ITT) participants to provide 80 % power at a two-sided 5% α-level (G*Power; Faul et al., 2007; See Figure 3.3.1)

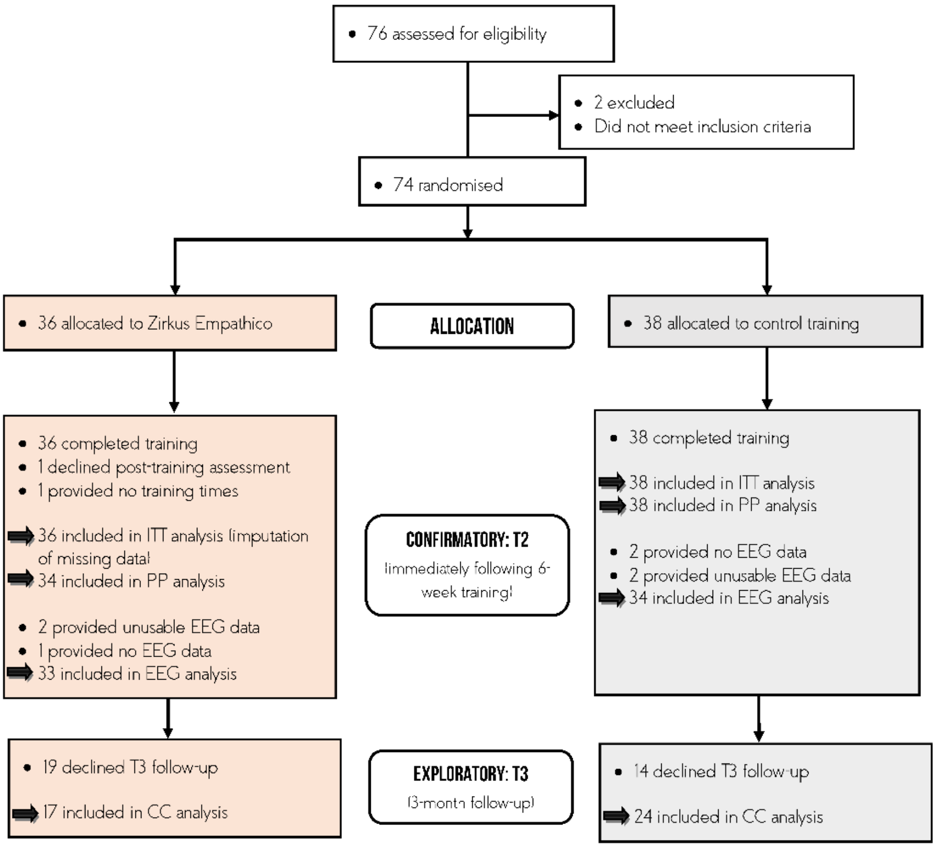


Figure 3.3.1 Flow Diagram of the trial. ITT = intention-to-treat, PP = per protocol, CC = complete cases.

We excluded participants with (a) a nonverbal IQ below 70 (Coloured Progressive Matrices, CPM; Raven, 2002), (b) verbal age under 4 years (Peabody Picture Vocabulary Test, PPVT; Dunn & Dunn, 2007) (c) autism symptomatology (Social Responsiveness Scale, SRS; cut-off > 76; Constantino & Gruber, 2005) (d) neurological or psychological disorders, (e) training- or EEG-impairing medication (e.g., stimulants), as well as (f) parallel participation in other socio-emotional trainings or clinical trials. All participants for the training group (N = 36) and control group (N = 38) were of Central European origin. To describe families' socioeconomic status (SES), we summarized family income, caregiver occupation, and education with the Winkler index (Winkler & Stolzenberg, 1998). Families' SES ranged from medium to high. There were no differences between groups in terms of their participant characteristics. Table 3.3.1 provides screening and demographic information.

Table 3.3.1 Baseline participant sociodemographic information.

Baseline characteristics		Controls (N= 38)	Zirkus Empathico (N= 36)
Sex	Female / Male	18 / 20	16 / 20
Age	Years *M (SD)*	5.1 (0.9)	5.1 (0.8)
SES (Winkler Index)	Low *n* (%)	3	3
	Medium *n* (%)	24	20
	High *n* (%)	73	77
Siblings	No siblings *n* (%)	11	19
	Up to two siblings *n* (%)	87	69
	More than two *n* (%)	2	12
Verbal age	PPVT percentiles *M (SD)*	68.5 (24.8)	68.4 (25.0)
Nonverbal IQ	CPM score *M (SD)*	14.8 (3.7)	13.9 (3.4)

Note. SES = socioeconomic status (Winkler Index), PPVT = Peabody Picture Vocabulary Test, CPM = Coloured Progressive Matrices.

Procedure

Baseline SEC was examined with child assessments and parent ratings prior to training assignment at the study center. Eligible participants were randomly allocated to the Zirkus Empathico or control group accounting with covariate-adaptive allocation accounting for the covariates age (below vs. above 5.3 years) and gender (male vs. female, carried out with QMinim; probability method: biased coin minimization; base probability: 0.8; Saghaei & Saghaei, 2011). Due to the nature of the training, families could not be blinded to allocation status. However, study advertisement indicated to provide both early language and SEC trainings. Consequently, the focus of the study was revealed to the families only after they had completed the study. Parents of both groups gave written and informed consent, received on-site instructions and a training manual. The manual entailed information on the handling of the tablet-PC (e.g., how to start the application, change the volume or charge the tablet-PC) as well as task descriptions of the respective training. Parents were asked to only assist their child during the training in case of questions (e.g., if the child did not understand the task and thus would have otherwise not been able to continue with the training) or technical problems (e.g., if the tablet-PC could not open the application). Thus, joint interactions with the training were kept to a minimum. Each family received a tablet-PC with the assigned touchscreen application to practice at home. Training lasted six weeks, with a weekly engagement of minimum 60 minutes. The *Screen Time* tracking application (Screen Time Labs) was used to monitor training engagement and to limit daily training time to 30 minutes. After six weeks of training at home, parent ratings and child assessments were repeated at the study center by an evaluator who was blind to group assignment. Furthermore, children participated in an EEG task. In addition to the pre-registered procedure, we explored possible implications of the Zirkus Empathico training by re-assessing children's SEC with online parent reports in a follow-up three months after training completion.

Intervention

As shown in Figure 3.3.2, Zirkus Empathico targets awareness and differentiation of own and others' emotions, empathy, and prosocial behaviors through interactions with naturalistic video sequences of facial expressions and social situations (Kirst et al., 2022; Kirst et al., 2015). The child can practice with different modules: In the first module, the child specifies inner emotional states associated with a specific context by using a virtual emotion manikin. The manikin constitutes a central element of the training to support the child in expressing perceived emotions on a two-dimensional scale indicating arousal and valence levels. Within the second module, the child is asked to identify emotion labels for facial expressions of adult and child protagonists (emotions: happy, sad, angry, anxious, and surprised). The third module offers possibilities to understand emotion eliciting contexts. Emotion-inducing video clips visualize the emotion-eliciting context of another person; the child's task is to identify the emotional state of this person. Within the last module, the child is presented with a third person's emotional expression embedded in an emotion-triggering context. Afterward, the child can decide how to react to the other person (e.g., go and talk to this person), fostering empathy and prosocial actions (See Description S3.2.1 for further details).

As control training, we employed the touchscreen application Squirell & Bär (the Good Evil GmbH), which fosters early foreign language acquisition through the interaction with basic English words and phrases (Note: Our sample included native German speakers without prior knowledge of English). The application invites the child to accompany a squirrel and a bear whose mission it is to save bees from extinction. The child can fulfill tasks in which he or she helps other animals (e.g., feed a badger or find a certain object for a beaver), which in return provide hints to save the bees. Throughout the mission, objects are more and more referred to in English words, allowing the child to acquire basic English words. For repetition of vocabulary, there is a virtual sticker book containing animals and objects which the child encountered during the mission. We chose this application as control training because of its comparability in terms of training length, intensity, cognitive demands as well as parental involvement.

Figure 3.3.2 Training elements of Zirkus Empathico. Left: Exemplary module sequence of identifying other people's facial expressions. Middle: Overview of different training modules targeting own and others' emotion recognition from situational cues; empathy and prosocial actions.Right: Interactive manikin to visualize own and other's emotional states with sliders for valence and arousal (Kirst et al., 2022; Kirst et al., 2015). Consent to publish all images was obtained from the individuals who are displayed here as part of the Zirkus Empathico training.

Measures

Primary outcome: Empathy. Pre- and post-training, parents filled out the *Griffith Empathy Measure* (GEM) Dadds et al., 2008 which includes 23 items addressing both cognitive and affective facets of empathy (e.g., affective empathy: "My child cries or gets upset when seeing another child cry."; cognitive empathy: "My child can't understand why other people get upset.") Dadds et al., 2008. Items were rated on a nine-point Likert scale from strongly disagree (-4) to strongly agree (+4). The internal consistency of the GEM in our sample at baseline and T2 (immediately following 6-week training) was sufficient (T1: Cronbach's α = .64; T2: Cronbach's α = .72). Previous literature likewise indicated good convergence with child ratings and sufficient reliability (Cronbach's α = .81) Dadds et al., 2008. To complement GEM findings, we used parent ratings and child assessments of the *Inventory to survey of emotional competences for three- to six-year-olds* (EMK 3-6; Petermann & Gust, 2016). The parental questionnaire consists of 17 items (subscales: empathy (8 items), emotion recognition (4 items), reward deferral (5 items) [not part of this study], which were rated on a four-point Likert scale (e.g., empathy: "The child reacts affected if someone is sad."). The child assessment includes tasks on perspective taking and emotion sharing. Children had to take a doll's perspective in different situations (e.g., the doll is afraid of dogs, what happens if the doll meets a dog?). They had to express and justify actions to help the doll (e.g., to chase the dog away if the doll is afraid of dogs). According to Gust et al. (2017), the EMK 3-6's internal consistency (Cronbach's α = .78-.90) and construct and criterion validity have been found to be sufficient. These observations match our internal consistency findings (parent ratings T1: Cronbach's α = .81, T2: Cronbach's α = .96; child assessment: T1: Cronbach's α = .86, T2: Cronbach's α = .84).

Secondary outcome: *Emotion recognition.* We used the child assessment and parent rating (example item: "The child understands and uses emotion words.") of the EMK 3-6 to examine emotion recognition abilities. Children had to recognize other children's emotions on picture cards and name the mimic markers of these emotions (e.g., raised eyebrows for surprised faces). All EMK 3-6 child assessments entailed practice rounds first to ensure that the child understood the task.

Secondary outcome: *Prosocial behavior.* Prosocial behavior was examined with the EMK 3-6 child assessment (see EMK 3-6 empathy assessment description) and the 25-item parental report subscales prosocial behavior and reduction of problematic behaviors of the *Strengths and Difficulties Questionnaire* (SDQ; Goodman, 1997). The SDQ's concurrent and divergent validity and internal consistency was confirmed in a study with teacher and parent ratings of preschoolers (Cronbach's α = .77) Mieloo et al., 2012. We also detected sufficient internal consistency at baseline (Cronbach's α = .77) as well as T2 (Cronbach's α = .92).

Secondary outcome: Neuronal sensitivity to facial expressions. We recorded EEG, while participants observed faces of happy, angry, and neutral expressions. Face stimuli depicted both male and female adults from standard face databases (Radboud Faces Database: Langner et al., 2010; Chicago Face Database: Ma et al., 2015). Faces were grey-scaled, adjusted to mean luminance, and trimmed to an oval shape excluding hair and non-facial ´contours (height: 150 pixels, width: 110 pixels). They were presented on a grey background (RGB = 100, 100, 100) using a 15`` monitor (display resolution: 1024 x 767) in a distance of 70 cm (visual angle: 3.27°). The task was administered using the software Presentation® (Neurobehavioral Systems, Inc., Berkeley, CA, www.neurobs.com). For each trial, a fixation cross was on screen for 500 ms, followed by a blank screen with a jittered inter-stimulus-interval (400-600 ms), a face stimulus (1,000 ms) and a blank screen as inter-trial-interval (1,000 ms). We presented three blocks with 60 trials each (180 trials total). Within blocks, no condition, gender or valence was repeated more than three times successively. 13% of the trials displayed ape faces instead of human faces. Participants were asked to press a button when they saw an ape face (overall accuracy: M = 72.30 % (27.97)). Ape face trials were used to ensure children's attention and were not analyzed further. Ten practice trials that included ape and human faces preceded the test session to ensure that the child understood the task.

Additional analyses: Training time, fidelity and satisfaction. We used Screen Time to measure children's training time. Additionally, parents recorded the training time in a paper-based diary. Since Screen Time tracking data was not provided or accurate enough for 27 % of the sample (e.g., due to technical issues), we used parent ratings as training time estimations (Correlation between parent ratings and tracking times ($r(49) = .46$, $p < .001$). Post-training, parents evaluated parent engagement, children's level of acceptance and satisfaction as well as implementation into daily life by rating several items on a five-point rating scale and by answering open-ended questions (See Table S3.3.1).

EEG recording, processing, and analysis

We recorded continuous EEG data with in-house QRefa Acquisition Software (Version 1.0 beta; MPI-CBS, Leipzig, Germany) using a Refa amplifier system (Twente Medical System International B.V). EEG signal was collected from 46 Ag/AgCl electrodes, according to standard positions (International 10-20 system of electrode placement; see Figure 3.3.3) held on an elastic cap (EasyCap GmbH, Germany). EEG data were sampled at 500 Hz and online-referenced to CZ (ground electrode at Fp1). Electrode impedances were kept below 10 kΩ; electro-oculograms were registered with electrodes at the outer canthi of both eyes and at the orbital ridge of the right eye. We carried out further offline pre-processing in accordance with previous recommendations for EEG studies (Keil et al., 2014) employing MATLAB (Version: 2016b) with its toolboxes EEGlab (Delorme & Makeig, 2004) and ERPlab (Lopez-Calderon & Luck, 2014). Data was high-pass filtered at 0.01 Hz, low-pass filtered at 30 Hz (IIR Butterworth 2nd order filter) and notch-filtered at 50 Hz (Parks-McClellan Notch filter). Subsequently, EEG data was re-referenced to the average of all data channels (excluding eye channels). We removed ocular artifacts based on an independent component analysis (ICA, EEGLAB: runica algorithm) results. Afterwards, data were segmented from 200 ms before stimulus onset to 1,000 ms post-stimulus onset and baseline-corrected using the mean activity during the 200 ms prior to stimulus onset. Based on artifact rejection procedures of ERP studies with preschool samples D'Hondt et al., 2017, segments that still contained artifacts were removed based on a semi-automated artifact rejection of voltage (exceeding ± 200 µV) and visual inspection of each trial. No differences between number of trials per facial expression were detected ($F(2, 177) = 0.01$, $p = .99$; happy: $M = 49.02$ (10.12); angry: $M = 49.23$ (10.27) and neutral: $M = 49.08$ (9.58)).

Regions of interest were selected based on previous research (Batty & Taylor, 2006) and confirmed by visual inspection of averaged ERP topographies across all conditions. P1 and P3 were quantified at electrodes PO3, PO7, PO9, O1, O2, Oz, PO4, PO8, PO10, and the N170 at electrodes P7, TP7, CP5 and P8, TP8, CP6. P1 peaks were determined in the time window of 90 to 130 ms; N170 peaks from 180 to 220 ms after stimulus onset. Individual P1 and N170 peaks were identified using peak detection procedures and quantified as mean amplitude in the time window of 20 ms surrounding the individual peak. The P3 was quantified as mean activity between 300 to 500 ms after stimulus onset.

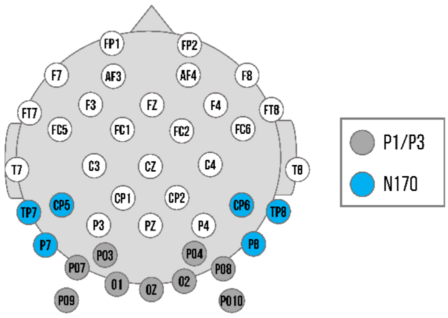


Figure 3.3.3 Electrode montage with channel locations used as regions of interest (ROIs). Dark grey: Channels used for the P1 and P3 component. Blue: Channels used for the left and right ROI of the N170 component.

Data analysis

Statistical analyses were performed using R-Studio (R Core Team, 2019 version 4.0.2) and reported according to CONSORT guidelines (Schulz et al., 2010). Study-related data and code can be found in an open-access repository.

Confirmatory analysis

Hypotheses and methods were specified within the pre-registration. Our analysis plan was adapted from pre-existing intervention studies (Siebelink et al., 2022). To investigate both the effect of the assigned and actually received intervention, the analyses of primary and secondary outcomes were based on ITT and per-protocol (PP) samples (See Figure 3.3.1). Missing data (N = 1) were imputed by multiple imputation with chained equations (MICE; mice R package version 3.13.0) employing predictive mean matching (Morris et al., 2014; number of imputation sets $m = 50$). All primary and secondary endpoints as well as group, age, and sex were integrated as predictors in the imputation model.

For primary and secondary outcomes, we calculated change scores as the difference between participants' pre-training (T1) and post-training (T2; immediately following the 6-week training) parent rating and child assessment scores. Subsequently, for ITT and PP samples, we carried out separate analyses of covariance (ANCOVAs) for each primary and secondary outcome with change score as dependent variable and training as between factor, covarying for participant's pre-training scores. We report Cohen's d as effect size (small effect = 0.2; medium effect = 0.5, large effect = 0.8; J. Cohen, 1988). Results of primary and secondary outcomes did not change when controlling for training time (See "https://naumsand.github.io/zerp/" under "Confirmatory Analysis").

For the analysis of the P1, N170, and P3 at T2, we excluded participants without an EEG measurement at post-training (N = 3) or too few ERP trials (below 10 trials; N = 4; J. Bruce et al., 2021). We computed separate analyses of variance (ANOVAs) on participants with sufficient EEG data quality (Zirkus Empathico N = 33; Controls N = 34) with ERP amplitude as dependent variable, training as between factor, and facial expressions (happy vs. angry vs. neutral) as within factor.

Complementary analysis

In addition, we also carried out complementary analysis to explore possible effects three months after training completion and associations between behavior and brain variables. We examined training fidelity differences between groups with Welch's t-tests (tadaatoolbox R package version 0.17.0). Exploratory follow-up analyses were conducted with a complete case (CC) sample including families who completed T1, T2 as well as T3 (three-month follow-up) parent ratings (Zirkus Empathico N = 17; Controls N = 24). This procedure was chosen because with a data loss of 44.6 %, imputation would have been likely to be biased (Armijo-Olivo et al., 2009). We computed change scores as the difference between participants' pre- and post-training parent rating scores (T1-T2 and T1-T3). Subsequently, we calculated separate ANCOVAs for each primary and secondary parent outcome with change score as dependent variable, training as between factor and time as within factor (T1-T2 vs. T1-T3), covarying for participant's pre-training scores. Lastly, we performed exploratory correlational analyses using Pearson's correlations across with the sample of the ERP analysis to associate brain and T2 behavior variables which yielded training-induced changes.

3.3.3 Results

Confirmatory analyses: Primary outcome

As shown in Figure 3.3.4, we did not detect group differences for empathy measured by the GEM parent rating (GEM_P ITT: $d = 0.23$, 95% CI [-0.23, 0.70], $p = .32$; PP: $d = 0.20$ [-0.26, 0.68], $p = .35$). In contrast, EMK 3-6 parent ratings indicated larger increases in empathy for the Zirkus Empathico group compared to controls (EMK EM_P ITT: $d = 0.28$ [-0.17, 0.76], $p = .045$; PP: $d = 0.32$ [-0.15, 0.80], $p = .02$). However, no difference was found for EMK child assessments (EMK EM_{CH} ITT: $d = 0.29$ [-0.016, 0.77], $p = .07$; PP: $d = 0.28$ [-0.19, 0.76], $p = .09$; see Figure 3.3.5 for distribution information).

Confirmatory analysis: Secondary outcomes

Emotion recognition. As shown in Table 3.3.2, child EMK 3-6 assessments yielded significantly larger increases for emotion recognition in the Zirkus Empathico group compared to controls (EMK ER_{CH}: ITT: $d = 0.57$ [0.01, 1.06], $p = .006$; PP: $d = 0.54$ [0.08, 1.04], $p = .01$), whereas parent ratings did not reveal significant results (EMK ER_P ITT: $d = 0.04$ [-0.42, 0.50], $p = .15$; PP: $d = 0.05$ [-0.42, 0.52], $p = .05$).

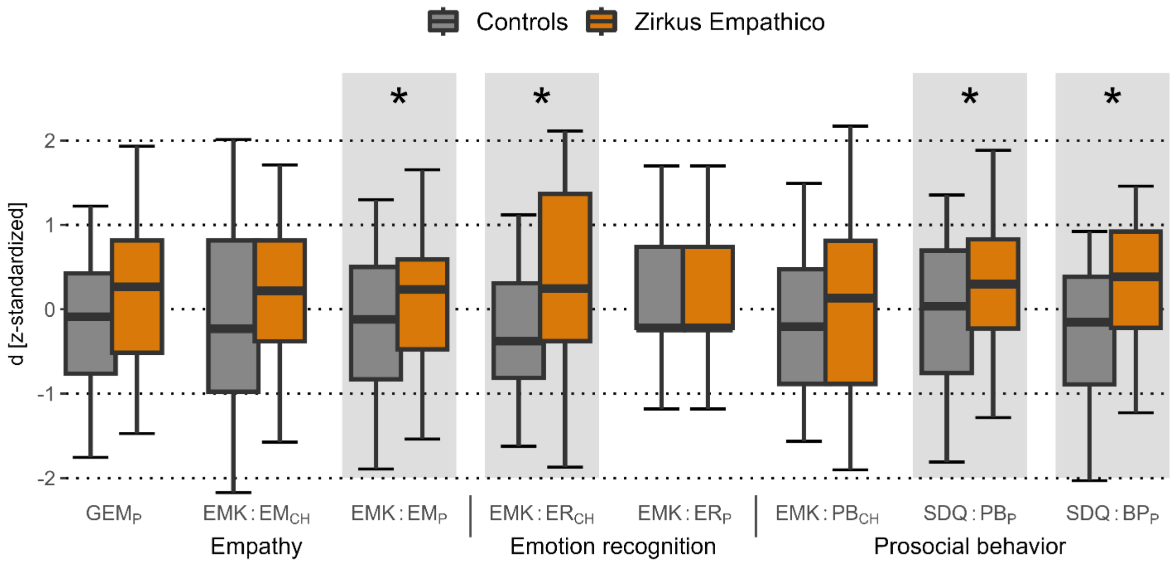


Figure 3.3.4 Parent and child ratings of socio-emotional competence (SEC) reports. Orange: Zirkus Empathico group. Grey: Control training. Error bars indicate standard errors (SE); center line represents median; upper and lower box limits represent quartile 1 and quartile 3; whiskers represent minimum and maximum values; d z-standardized represents the standardized change scores (difference between post- and pre-training values). Note: Standardization was achieved by subtracting each value from the variables mean and dividing them by the variable's standard deviation ($x - \bar{x}$) /SD). Standardization was only carried out for visualization purposes; statistical analyses were carried out wih the raw d values. GEM = Griffith Empathy Measure; EMK = Inventory to survey of emotional competences for three- to six-year-olds; EM = Empathy; ER = Emotion recognition; SDQ = Strength and Difficulties Questionnaire; PB = Prosocial behavior; BP = Behavioral problems. P = parent rating; CH = child assessment. Asterisk (*) indicates significant difference with p-value < .05 calculated within separate ANCOVAs for each outcome.

Prosocial behavior. The EMK 3-6 child assessment for prosocial behavior did not display group differences (EMK PB_{CH} ITT: $d = 0.02$ [-0.44, 0.48], $p = .57$; PP: $d = 0.04$ [-0.43, 0.51], $p = .54$). SDQ parent ratings, however, showed larger increases in prosocial behavior (SDQ PB_P ITT: $d = 0.51$ [0.05, 0.99], $p = .008$; PP: $d = 0.46$ [-<0.01, 0.95], $p = .004$) and greater declines in problem behavior for the Zirkus Empathico group compared to controls (SDQ BP_P ITT: $d = 0.54$ [0.08, 1.03], $p = .01$; PP: $d = 0.62$ [0.16, 1.12], $p = .01$).

Table 3.3.2 Outcome measures at baseline (T1) and after training (T2).

	Controls (N = 38)			Zirkus Empathico (N = 36)					
Parental rating									
	T1	T2	D (T2-T1)	T1	T2	D (T2-T1)	*F* value	*p*	Cohen's *d* [95% CI]
Empathy (GEM_P)	15.95 (14.90)	14.11 (18.07)	-1.84 (13.45)	15.47 (13.19)	16.92 (15.21)	1.44 (14.76)	0.99	.32	0.23 [-0.23, 0.70]
Empathy (EMK EM_P)	17.76 (3.17)	17.71 (3.35)	-0.05 (2.82)	19.00 (3.55)	19.75 (3.36)	0.75 (2.80)	4.14	**.045**	0.28 [-0.17, 0.76]
Emotion recognition (EMK ER_P)	10.29 (1.64)	10.50 (1.33)	0.21 (1.21)	10.89 (1.37)	11.14 (1.07)	0.25 (0.84)	2.13	.14	0.04 [-0.42, 0.50]
Prosocial behavior (SDQ PB_P)	5.37 (1.50)	7.32 (1.74)	1.95 (2.08)	5.31 (1.62)	8.25 (1.34)	2.94 (1.55)	7.50	**.008**	0.51 [0.05, 0.99]
Problem behavior (SDQ BP_P)	15.89 (3.14)	9.24 (3.76)	6.66 (3.22)	15.75 (3.75)	7.22 (3.28)	8.53 (4.02)	7.01	**.009**	0.54 [0.08, 1.03]
Child assessment									
Empathy (EMK EM_{CH})	10.53 (3.51)	11.32 (3.79)	0.79 (3.45)	11.32 (3.06)	13.11 (3.30)	1.78 (3.21)	3.50	.07	0.29 [-0.02, 0.77]
Emotion recognition (EMK ER_{CH})	16.00 (5.05)	17.42 (4.75)	1.42 (2.78)	16.19 (4.18)	19.86 (4.42)	3.67 (4.78)	7.98	**.006**	0.57 [0.01, 1.06]
Prosocial behavior (EMK PB_{CH})	11.82 (3.44)	13.39 (2.96)	1.58 (2.73)	12.28 (2.17)	13.92 (2.42)	1.64 (3.20)	0.33	.57	0.02 [-0.44, 0.48]

Note. Pre-registered baseline (T1) and post-training (T2) outcomes as means (SD) from ITT analyses (see DRKS-ID: DRKS00015789). D = difference score between T2 and T1 (except for problem behavior where T1-T2 was calculated as the score is inverted). F and p-values refer to the training main effect from the ANCOVAs without training time. GEM = Griffith Empathy Measure; EMK = Inventory to survey of emotional competences for three- to six-year-olds; EM = Empathy; ER = Emotion recognition; SDQ = Strength and Difficulties Questionnaire; PB = Prosocial behavior; BP = Behavioral problems. P = parent rating; CH = child assessment. All p-values are uncorrected.

ERP measures. ERP trajectories and associated topographies are displayed in Figure 3.3.6. For the P1, no training effect ($d = 0.19$ [<0.01, 0.60], $p = .43$), but a main effect of facial expression was found ($d = 0.16$ [<0.01, 0.37], $p = .01$). P1 amplitudes were larger for happy vs. neutral faces ($p = .008$). We detected no amplitude differences for angry vs. neutral faces ($p = .11$), or for happy vs. angry faces ($p = .56$). The interaction of training and emotion did not yield significant results ($d = 0.08$ [<0.01, 0.20], $p = .30$). N170 amplitudes were neither modulated by training ($d = 0.08$ [<0.01, 0.12], $p = .73$), facial expression ($d = 0.07$ [<0.01, 0.10], $p = .66$), nor their interaction ($d = 0.07$ [<0.01, 0.18], $p = .63$; due to a lack of N170 hemispheric differences averaged ROI results are reported). Concerning the P3, we did not detect a main effect of training ($d = 0.03$ [<0.01, 0.05], $p = .89$), but a significant effect of facial expression ($d = 0.12$ [<0.01, 0.31], $p = .03$).

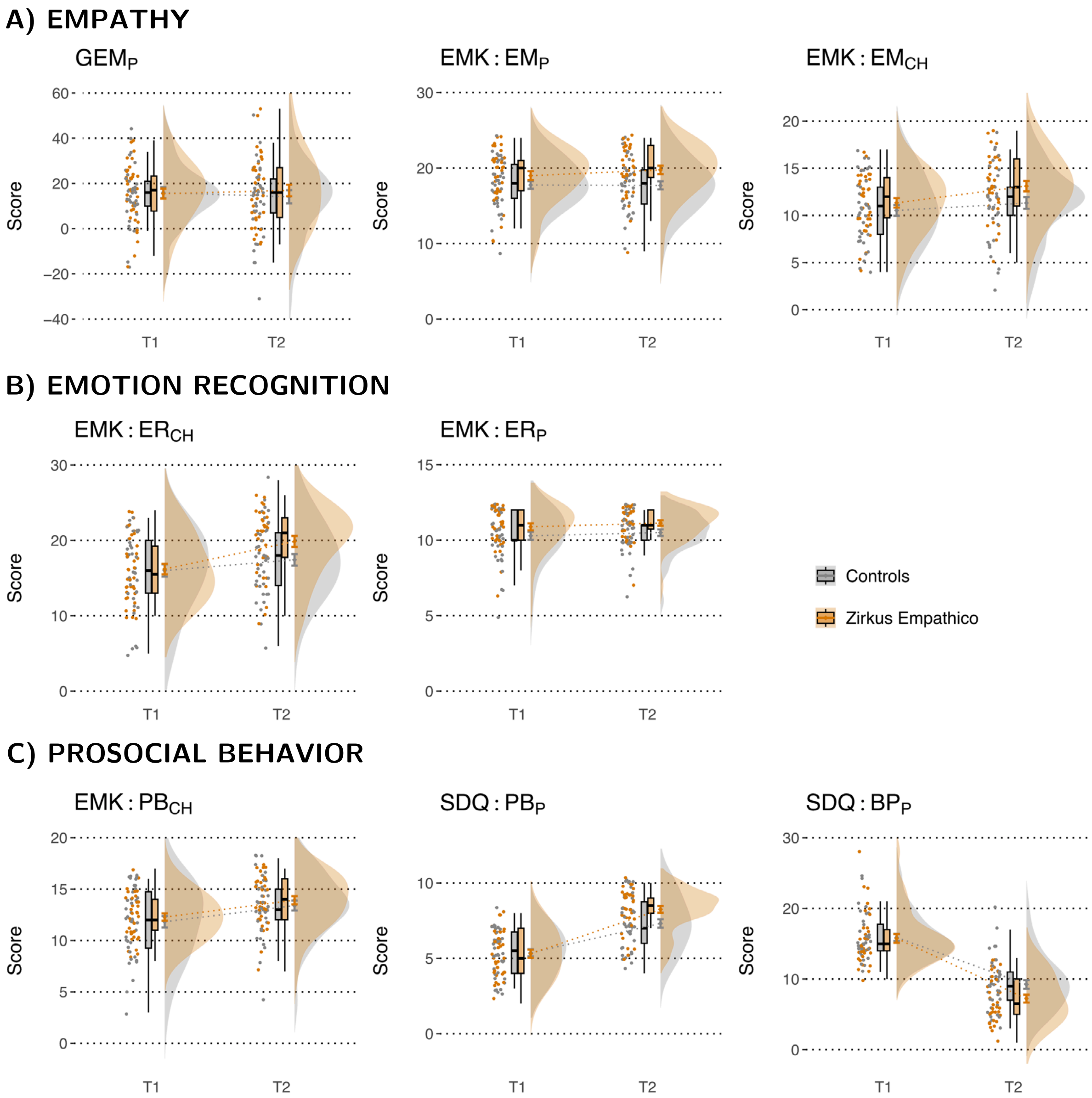


Figure 3.3.5 Distribution information on parent and child ratings of socio-emotional competence (SEC) reports. Orange: Zirkus Empathico group. Grey: Control training. Small boxplots: Error bars indicate standard errors (SE); center line represents median; upper and lower box limits represent quartile 1 and quartile 3. Small line plots: Error bars indicate standard error (SE); center line represents mean. GEM = Griffith Empathy Measure; EMK = Inventory to survey of emotional competences for three- to six-year-olds; EM = Empathy; ER = Emotion recognition; SDQ = Strength and Difficulties Questionnaire; PB = Prosocial behavior; BP = Behavioral problems. P = parent rating; CH = child assessment.

P3 amplitudes were larger for happy vs. neutral faces ($p = .02$), while P3 amplitude differences for angry vs. neutral faces ($p = .29$) or happy vs. angry faces were not statistically significant ($p = .29$). The facial expression main effect was qualified by an interaction with training (d = 0.11 [<0.01, 0.30], p = .04). The Zirkus Empathico group showed larger P3 amplitudes for happy vs. neutral faces (p = .01) and happy vs. angry faces (p = .02). None of the other post-hoc tests yielded significant results (all p > .16).

Complementary analysis

Training fidelity. Both groups showed high levels of training motivation with similar training engagement across groups (total time used in minutes: Controls M = 323.76 (127.95), Zirkus Empathico M = 351.21 (122.52); t(69) = -0.92, p = .36). Parental engagement did not differ between groups (rating from 1-5: Controls M = 3.38 (1.20), Zirkus Empathico M = 3.11 (1.40); t(70) = 0.85, p = .40). Parents also indicated that the training was compatible with daily routines (see Supplementary Material Table S3.3.1).

Exploration of follow-up effects. With a response rate of 55.4 %, results of the follow-up assessment are only interpretable to a limited extent: For the GEM parent rating, we detected a group effect (d = 0.77 [0.21, 1.31], p = .002) with larger increases in empathy for the Zirkus Empathico group compared to controls from T1 to T3. None of the other outcomes significant changes over time (See Table S3.3.2).

SEC measure associations with P3 amplitudes. We correlated post-training (T2) values of SEC measures, which indicated training-induced changes (EMK $EM_{\boldsymbol{P}}$, EMK $ER_{\boldsymbol{CH}}$, SDQ $PB_{\boldsymbol{P}}$, SDQ $BP_{\boldsymbol{P}}$) with P3 amplitude difference scores, which were sensitive to training group differences (happy minus neutral; happy minus angry). We did not detect any significant correlations (all p > .11; see Table S3.3.3).

3.3.4 Discussion

Digital technology offers new ways of transforming preventative and therapeutic spaces to bridge the mental health gap for children, particularly in times of the COVID-19 pandemic when children lack face-to-face social interactions and learning opportunities. In the current study, we evaluated the effectiveness of the digital SEC training Zirkus Empathico over the course of six weeks in preschool children. The training group, as compared to the active control group, showed gains in parent empathy ratings, child assessment scores of emotion recognition, parent ratings of prosocial behavior, and reduced problem behavior directly after the training. As further secondary outcome, we complemented the behavioral measures with neuronal markers examining training-induced emotion processing changes in sensory (P1, N170) and higher-order (P3) ERPs.

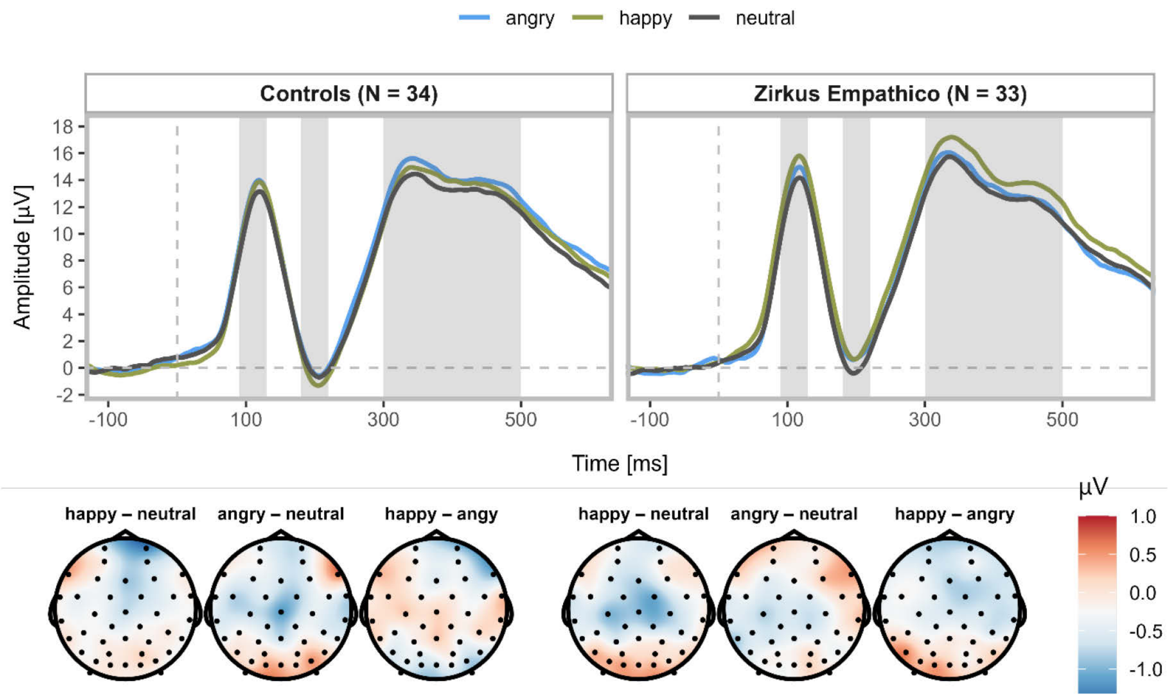


Figure 3.3.6 ERP trajectories and morphologies for the control and Zirkus Empathico group. Averaged P1, N170 and P3 waveforms for happy (green), angry (blue) and neutral (grey) facial expressions (ROI P1/P3 electrodes: PO3, PO7, PO9, O1, O2, Oz, PO4, PO8, PO10; ROI N170 electrodes: P7, TP7, CP5 and P8, TP8, CP6. Shadowed areas indicate the time windows used to identify participants' individual peaks and mean amplitudes. Topographies summaries the averaged P3 activity (300-500 ms) displaying amplitude difference scores for facial expression contrasts (from the left): Controls happy–neutral, angry–neutral and happy-angry; Zirkus Empathico group happy–neutral, angry–neutral and happy-angry.

Training-induced changes were visible for higher-order processing stages associated with emotion sensitivity: The Zirkus Empathico group showed larger P3 amplitudes for happy vs. neutral and angry faces. Exploratory analyses of a three-month follow-up indicated gradual increases in parent empathy ratings for the Zirkus Empathico group over time.

In line with our hypothesis, the Zirkus Empathico group, compared to controls, showed improvements in one of the measures chosen for the primary outcome empathy, reflected by greater increases in the EMK 3-6 empathy parent rating. This finding resonates with previous research reporting improvements in empathy after preschoolers engaged with a digital SEC training in the classroom setting (Wu & Kim, 2019). Interestingly, no training group differences were detected for the GEM empathy parent rating as further primary outcome. The reason for this discrepancy might lie in the fact that the EMK 3-6, in contrast to the GEM, includes items for prosocial behavior associated with empathic processing (e.g., comfort someone when he or she is sad). This might indicate that Zirkus Empathico fostered preschoolers empathy specifically in children's direct actions toward others.

In concordance, we detected in some of our measures increases in our secondary outcomes prosocial behavior and emotion recognition, and reductions of behavioral problems after the training for the Zirkus Empathico group, which is in line with previous studies using classroom SEC trainings (Wadepohl et al., 2011). The delivery of the training content (e.g., naturalistic videos of facial expressions) may have triggered an authentic perception of social cues (Kliemann et al., 2013; Wu et al., 2020) . Additionally, as suggested by parent fidelity ratings, children were highly motivated to engage in the Zirkus Empathico training and families needed minimal effort to implement the training into their everyday lives'.

As further secondary outcome, we examined facial expression processing with early and late ERPs. Contrary to our hypothesis, our results did not suggest that the Zirkus Empathico training affected early stages of facial expression processing. Further, at later processing stages, the result pattern did not match our hypothesis: P3 amplitudes were larger for happy vs. angry and neutral facial expressions in the Zirkus Empathico group, but controls did not show significant P3 amplitude modulations by facial expressions nor differences to the Zirkus Empathico group. One possible post-hoc explanation for the larger P3 amplitudes for happy faces could be that the Zirkus Empathico group allocated more processing resources toward positive emotional stimuli. Previous research linked the P3 to emotion regulation processes (Hajcak et al., 2010), suggesting that Zirkus Empathico might lead to reorientation processes towards positive emotional states, which has been identified as effective regulation strategy (Tugade & Fredrickson, 2007). Allocating more attention to positive images may also serve as a protective factor to avoid maladaptive affective responses (Lagattuta & Kramer, 2017). This neuronal pattern parallels reported improvements of the Zirkus Empathico group for empathy and prosocial behavior as well as previous research on this digital training reporting emotion regulation improvements (Kirst et al., 2022).

Within our first exploration of possible effects three months after training completion, we found that children's capacity of empathy, i.e., their understanding of others' feelings seem to have increased over time, with stronger effects arising months after the training ended ("sleeper effect"; Blewitt et al., 2018), while improvements in emotion recognition and prosocial behaviors were not maintained in the long run. For some facets of SEC, the training intensity may have been too low for sustainable transfer into daily family interactions. Given the exploratory nature of the follow-up analyses, this data should be interpreted as tentative. Further, the chosen complete cases analysis which included only half of the sample favors a subset of the study's participants which may also hamper generalizability of the findings.

Further research is needed to investigate how sustainable transfer from digital SEC trainings can be accomplished. While our home-based training spanned only six weeks, typical classroom-based SEC trainings which have proven effective were realized over several months up to a year (Wadepohl et al., 2011). Thus, future studies should examine the effectiveness of long-term digital SEC trainings. In addition, the children of our study practiced with minimal parental guidance. However, as indicated by a previous Zirkus Empathico training study, parental involvement might enhance transfer into daily life with parents serving as a role model (Kirst et al., 2022). Thus, further research could compare the transfer effects of the Zirkus Empathico training varying the amount of parental involvement. As suggested by the ERP findings, further research would also profit from an in-depth understanding of how emotion regulation plays into the mechanisms of the training by e.g., an integration of an emotion regulation based EEG paradigm.

Taken together, Zirkus Empathico seems to be effective in enhancing brain and behavioral measures associated with SEC in preschoolers, indicating the potential of this digital training to be used as an educational tool in children's home settings. According to a framework Hirsh-Pasek et al. (2015), Zirkus Empathico is best seen as a "second wave app". These applications aim to create digital learning experiences which are active, engaging, meaningful and socially interactive. We rated the Zirkus Empathico training based on these criteria and found that it scored in all four categories (See Description S3.3.1), which adds to the credibility of this program. Thus, as being easily accessible by the public with low costs, digital SEC trainings such as Zirkus Empathico could be implemented more widely as prevention strategies to reduce the risk for mental illness among children and adolescents. SEC trainings open the possibility to strengthen skills (e.g., creating meaningful relationships, recognizing and regulating emotions) which in return serve as protective factors for problematic behavior and to overcome social challenges (Alwaely et al., 2021; Colomeischi et al., 2022).

Zirkus Empathico has also been shown effective in a clinical sample of children on the autism spectrum (Kirst et al., 2022). Digital tools as a support to alleviate mental disorders have gained momentum in past years, given the wide accessibility and the potential to ease pressures on face-to-face health care services (Halldorsson et al., 2021). This is of special importance given that traditional trainings cannot be maintained when social contacts are severely reduced due to external circumstances , as has been the case in the COVID-19 pandemic (Patrick et al., 2020). Further, digital trainings might not only reach populations in health care-deprived areas but also populations which might otherwise not be wanting to seek help, e.g. to avoid stigma associated with visits to mental health services (Halldorsson et al., 2021). In addition, traditional classroom trainings may require trained professionals, whereas digital solutions are more flexible in terms of pace and timing of the training without necessarily needing an in-person instructor. Since children can repeat exercises as often as they want, digital trainings also offer the advantage of being more targeted toward their individual learning speed as compared to traditional classroom trainings.

As indicated by this study and previous research on Zirkus Empathico (Kirst et al., 2022) some remarks are necessary regarding the implementation of digital trainings: Young children increasingly engage with digital technology (Hollis et al., 2017) and delivering trainings online might contribute to their daily screen time. Thus, parental guidance and access restrictions provided by the training Reid Chassiakos et al., 2016 should be in place to monitor and control for excessive use. In addition, our training targets children's SEC, which most importantly needs to be transferred into the child's daily interactions. Thus, the SEC training should provide options to facilitate family participation to further help modelling effective social and learning interactions outside the digital training environment (Kirst et al., 2022; Reid Chassiakos et al., 2016).

The findings of this study have to be seen in light of some limitations. Firstly, one has to note that our training effects are partly based on parental evaluations likely prone to rater biases. In our study, however, parents only knew that their child would either train their language or social skills; the purpose of the app their children were actually practicing which was revealed only after the end of participation to reduce potential biases. In addition, we found sufficient, but low internal consistency of the GEM at T1 (Cronbach's $\alpha = .64$), which is in line with findings of previous studies Murphy, 2019. Thus, alternative measures of empathy specifically targeting young children such as the Empathy Questionnaire (EmQue; Rieffe et al., 2010; Sesso et al., 2021) should be considered for future studies.

Further, we were not able to map the exact neuronal trajectory before and after training because we acquired EEG measurements exclusively post-training. Considering that we employed an implicit EEG task to assess facial expression processing, we only have limited insights on how well children recognized the different facial expressions. In addition, our sample size calculation was based on previous digital training studies entailing effect sizes from behavioral outcomes. The effect sizes of our ERP results ranged in the area of smaller effects, thus, with our sample size, we might have not been able to uncover all meaningful effects, which should be accounted for in future studies. More generally speaking, a larger sample size should considered to confirm this study's results as significant effects could only be obtained for some of the measures. Given that we evaluated the training in a sample of middle to upper class families, this restricted SES range might also reduce our findings' generalizability. Lastly, our first attempts to correlate report and brain data did not yield any significant results, potentially due to a lack of power. Hence, future research may include a larger sample to reveal potential effects.

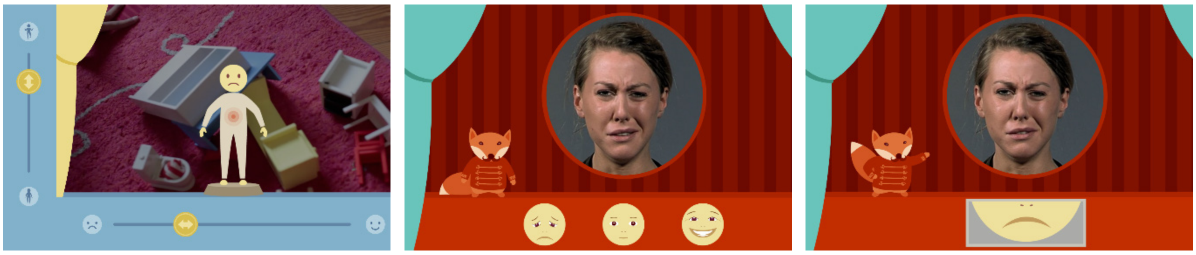
Our study highlights the potential of digital SEC trainings as preventative tools for young children's socio-emotional development. After six weeks of training at home, preschoolers showed improvements in empathy, emotion recognition, and prosocial behavior. Additionally, we detected disparate brain patterns between controls and the training group potentially indicating processing differences for happy facial expressions and thus providing first evidence of changes in neuronal plasticity through the SEC training. Further research is warranted to examine long-term transfer of these skills as well as the exact neuronal mechanisms behind the training-induced changes.

3.3.5 Supplementary Material

Description S3.3.1: Detailed description of the Zirkus Empathico (ZE) Training

Description of the ZE training

A B C

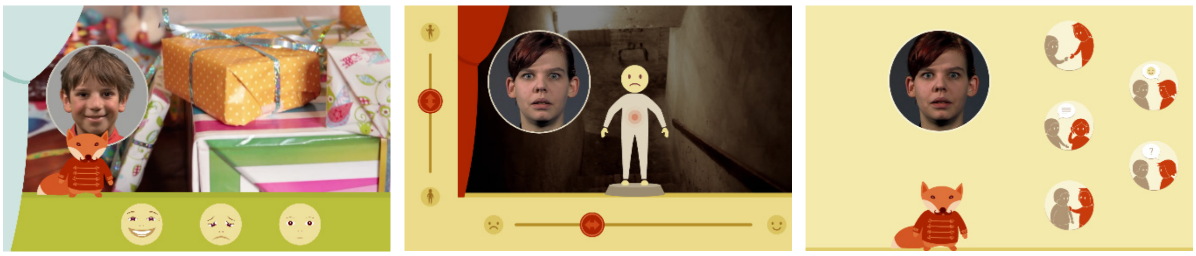


Fundamentally, the ZE training consists of 5 modules as well as an emotion library:

Module I – Awareness of own emotions: (A) By using the emotion manikin, the child can specify his/her inner emotional state regarding a specific context (emotion-inducing video clip). In a second step, the child describes his/her inner state by choosing an emotion label. The program provides feedback on whether the inner state and chosen emotion label are matched correctly or incorrectly.

Module II – Emotion recognition from faces: (B) The child is asked to identify the correct emotion label for the presented facial expression. (C) Unsolved tasks are repeated, with correct answers being prompted by visual hints after the first 2 wrong answers and an automatic correction after 3 wrong answers.

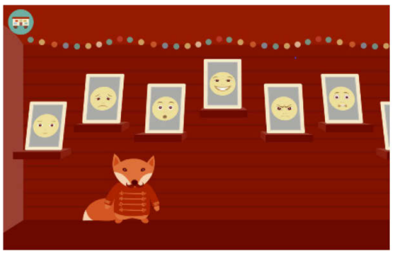
D E F



Module III – Understanding of emotion eliciting contexts: (D) The module requires the child to identify a specific emotion-eliciting context of another person. The child chooses the correct emotion label from 3 options. Unsolved tasks are repeated, with correct answers being prompted by verbal hints and a picture of the other person's emotional expression in response to the context.

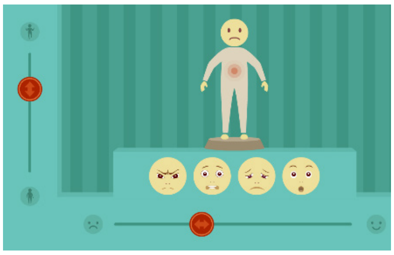
Module IV – Emotional empathy and prosocial action: (E,F) The stimuli show a third person's emotional expression embedded in the emotion triggering context. By using the emotion manikin, the child first evaluates its own emotional state, which may be influenced by the other person's emotional reaction to the given context. In a second step, the child is asked to choose between (a) approaching the person, (b) leaving the situation, or (c) waiting and seeing. If "approach" is selected, he/she is presented with a selection of concrete prosocial actions towards the other person (e.g. helping, being friendly, comforting, listening).

G



H

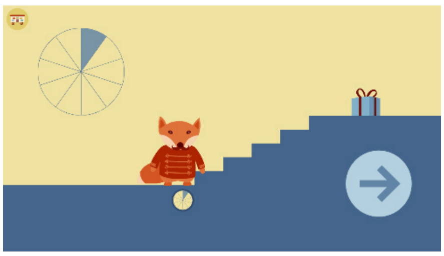
I



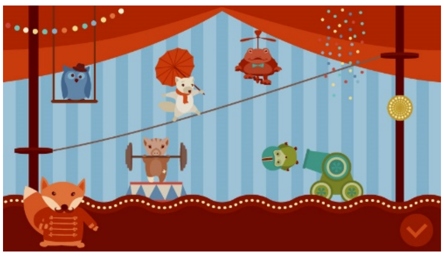
The library (G, H) contains explanations of the emotion manikin and the 6 emotion cards with definitions and explanations of the basic emotions/neutral states targeted. (1): Characteristic display of emotion in the eye/mouth region, synonyms for the emotion label, examples of emotion triggering contexts, arousal and valence of the emotion indicated by the manikin (2).

Emotion manikin/Generalization module: (I) The interactive manikin is a central element in the game which enables one's own inner emotional states and those of others to be visualized. The child can use two five-step sliders to indicate a) his/her level of bodily arousal (very calm – calm – neutral – aroused – highly aroused), and b) the valence of his/her feelings (very negative – negative – indifferent/neutral – positive – very positive). The manikin changes its movement and facial expression accordingly.

J



K



Level System and rewards: (J) The system indicates the child's progress within each module. Each level contains 10 tasks, which are displayed as a pie chart which is completed with the number of solved tasks. (K) When a level has been completed, the child is allowed to choose an animated reward, which is integrated into a circus arena. Extra rewards are hidden in boxes to enhance motivation

Design principles and usability testing. Following previous recommendations, the Zirkus Empathico training employs multi-media content such as videos, graphics and audio material (Williams et al., 2002). To allow children a self-determined training experience, a clear and unambiguous interface design without distracting details was employed; the training used precise wording as well as simple grammar and the audio information was visualized by icons or animations (Basil & Reyes, 2003). To maintain children's motivation, the ZE training includes immersive storylines, goals directed around targeted skills, rewards, and feedback about goal progress, and the provision of choice (Whyte et al., 2015). A first usability study of the ZE training was carried out with 11 typical developing children (7-12 years). The children were monitored during the gameplay and subsequently interviewed. The study confirmed an intuitive and self-determined use of the app and a good understanding of all relevant game elements (e.g., buttons, visual feedback, visualization of emotions). Within a second usability study, the prototype was presented to four autistic children (age: 10-12 years, all males) to analyze their application and understanding of the app over the course of four weeks. Children and their parents provided feedback on motivation, enjoyment, and attention during training and ideas which was used to further improve the training.

Training stimuli: Facial expression videos. The employed video sequences of adult facial expressions were taken from a previous project (Kliemann et al., 2013). For the ZE training, 170 videos depicting basic emotions (anger, fear, sadness, joy, surprise) and the neutral state were selected. Additionally, 78 videos of children`s emotional expressions (20 males, 58 females) were produced in the film studio of the Computer and Media Service (CMS) of *masked* with twelve children (4-13 years; naïve actors). The validation of the children`s emotional videos was carried out in a two-step procedure: First, invalid/non-believable videos were excluded during production by the third and last author. Second, the remaining video clips were validated by seven psychologists (age: M =29.9, SD = 3.6) working in the field of social cognition. The results showed high average emotion recognition rate (85.4%; SD = 17.3%) and sufficient believability on a six-point-rating scale form (1) not believable to (6) very believable (M = 3.9, SD = 1.0).

Training stimuli: Social situation videos. The production of the social situation videos for module I, III, and IV was based on interviews with 10 elementary school children (5 males, 5 females) between seven and eleven years, who were asked to describe own emotional experiences asociated with each of basic emotions. Appropriate narratives were selected and transformed into scripts for video production. Scripts either included social situations (e.g. anger: being bullied by children) or non-social situations (sadness: losing a teddy bear). Twelve non-professional actors (5 children, 7 adults) participated in the production of the short video clips (n = 56), each displaying emotion eliciting contexts targeting one of the basic emotions or a neutral state. All videos were filmed in first-person-perspective to allow the player of ZE to immerse into the respective situation as the agent. Six additional videos with creative commons licenses were also integrated, resulting in 62 video clips in total (length approx. 30-40sec). Each video is introduced in the respective ZE modules by an illustration and an audio sample (German) describing the background of the context (i.e.: Mod. I: "*Imagine you are at home. You are sick....*" or, respectively, Mod. III/IV: "*Imagine a child is at home...*"), the videos themselves are free of speech. An expert rating by three female psychologists working in the field of social cognition (age: $M = 28.7$, $SD = 2.3$) revealed sufficient validity of the stimuli (recognition rate of emotions elicited through situations: $M = 90\%$, $SD = 3\%$; mean confidence on a five-point-rating-scale from (1) not confident to have recognized the targeted emotion to (5) very confident: $M = 4.1$, $SD = 0.3$).

Qualitative evaluation of educational value. Hirsh-Pasek et al. (2015) provide a framework including four psychological pillars (active, engaged, meaningful, and social interactive learning) which can be helpful to determine the educational value of a digital application. In the following, the authors, have conducted a qualitative assessment of the Zirkus Empathico training based on these pillars:

<u>Active:</u> The Zirkus Empathico training fosters active (cognitive) engagement with different aspects: Firstly, it provides clear learning goals separated into four modules, which are guided by a fox, a digital avatar which accompanies and helps the child throughout the training. The fox eases the interaction of the child with the app, opening up different interaction options as well as helping the child to understand the application and its logical structure. In the same vein, access to the content is progressive, which allows the child to approach the content and its logic gradually. Children can navigate via intentional tap and swipe movements through the application (e.g., In some of the modules, children need to actively manipulate an emotion manikin to

express how they feel or how others feel, fostering their emotion knowledge and empathy skills.). All modules are self-explanatory (a parent can help, but is not necessarily required). The above-mentioned aspects of Zirkus Empathico foster the child's ability to work independently and follow along with the content while using the application.

Engaging: The Zirkus Empathico training approximates its main goal of acquiring socio-emotional competence skills through various elements The fox as an avatar of the training speaks to the child and motivates him or her to interact with the training content and directs the attention toward the relevant task aspects. The short video clips and vivid graphics support socio-emotional learning as the depicted social situations are shown realistically. All of the mentioned features are tailored toward the acquisition of socio-emotional competence skills so that children can engage fully in this goal without distraction

Meaningful: Within the training, children are presented with real-world images and video clips of social situations, which ease transfer to real-world situations. In addition, they receive meaningful feedback when they make a mistake (e.g., not classifying a facial expression correctly will result in the fox pointing to the parts of the face that facilitate the recognition of the emotion). When it comes to the evaluation of feelings (e.g., "How does this person feel in this moment?"), it is not about finding the "correct emotion", but more about matching the intended emotion with a matching emotion manikin. Thus, it also highlights that emotion are complex and that every person might interpret emotional cues differently, which is meaningful for interactions in everyday life. Lastly, the Zirkus Empathico training allows for parent-child interactions using the emotion library to talk about the child's feelings which offer various options to transfer into daily life.

Socially interactive: The training has a fox as avatar with which the child can have a parasocial interaction (Fox asks for example: "Are you still there?" if the child needs more than usual to answer or praises the child if he or she gave the correct answer). Furthermore, given the option to practice together with a parent, real social interactions are also possible. For example, the emotion manikin can be used as a tool to communicate feelings to a parent.

Table S3.3.1 Training fidelity items and results.

Measure	Zirkus Empathico N = 37*		Controls N = 35*		p
	M	SD	M	SD	
My child enjoyed the training.	4.34	0.87	4.00	0.97	.11
My child was motivated to do the training.	4.00	1.16	3.78	1.08	.3
My child trained mostly without me.	3.11	1.39	3.38	1.23	.4
The training was self-explanatory.	4.49	0.66	3.86	0.82	.001
The training was compatible with our daily routines.	4.31	0.93	4.32	0.85	>.09
My child copes better with his/her own feelings.	2.91	0.98	2.24	0.95	.008
My child is more interested in other languages.	1.51	0.95	3.05	1.45	<.001

Note. M: mean; *SD*: standard deviation. * Please note: 2 parent fidelity ratings are missing for this assessment; find additional fidelity measures here.

Table S3.3.2 ANCOVA T1-T2 vs. T1-T3.

Measure	$F(1,77)$	p	η_p^2
GEM$_P$			
- Group	10.05	.002	.12
- Time	0.42	.52	.01
- Group x Time	0.42	.52	.01
EMK EM$_P$			
- Group	0.40	.53	.01
- Time	0.17	.68	.002
- Group x Time	0.87	.36	.01
EMK ER$_P$			
- Group	1.37	.25	.02
- Time	0.27	.60	.004
- Group x Time	0.56	.46	.007
SDQ PB$_P$			
- Group	0.73	.40	.01
- Time	0.71	.40	.01
- Group x Time	0.92	.34	.01
SDQ BP$_P$			
- Group	3.11	.08	.04
- Time	3.27	.07	.04
- Group x Time	0.17	.69	.002

Note. GEM = Griffith Empathy Measure; EMK = Inventory to survey of emotional competences for three- to six-year-olds; EM = Empathy; ER = Emotion recognition; SDQ = Strength and Difficulties Questionnaire; PB = Prosocial behavior; BP = Behavioral problems. P = parent rating; CH = child assessment. All ANCOVAs included participant's baseline value as covariate.

Table S3.3.3 Correlational analyses.

P3 difference score happy-neutral correlation with...

	r	p
EMK EM$_P$	0.20	.11
EMK ER$_P$	0.05	.71
EMK ER$_{CH}$	0.004	.97
SDQ PB$_P$,	0.20	.11
SDQ BP$_P$	-0.09	.46

P3 difference score happy-angry correlation with...

	r	p
EMK EM$_P$	0.09	.49
EMK ER$_P$	0.02	.89
EMK ER$_{CH}$	0.16	.19
SDQ PB$_P$,	0.05	.67
SDQ BP$_P$	-0.11	.36

Note. Correlation coefficients were computed with Pearson's correlations. GEM = Griffith Empathy Measure; EMK = Inventory to survey of emotional competences for three- to six-year-olds; EM = Empathy; ER = Emotion recognition; SDQ = Strength and Difficulties Questionnaire; PB = Prosocial behavior; BP = Behavioral problems. P = parent rating; CH = child assessment.

4

Discussion and Implications

Think happy thoughts!

From the Disney movie "Peter Pan" (1953)

4. Discussion and Implications

The purpose of this dissertation was to assess the maturity and trainability of components relevant to the development of socio-emotional competence in preschoolers by integrating behavioral and neuronal measures. To contribute to the advancement of developmental and neurophysiological research as well as clinical prevention and intervention, three studies were conducted. In this chapter, I recapitulate and discuss the results of this dissertation. In addition, I draw conclusions regarding societal impact and future research opportunities.

4.1 Summary of Results

4.1.1 Preschoolers' Socio-Emotional Competence Development

In the introduction, I emphasized the importance of the preschool years for the development of socio-emotional competence. I displayed a cascade of developmental processes in which emotion recognition, particularly from facial expressions, comprises a fundamental skill that is essential for more complex processes of socio-emotional competence, such as empathic or prosocial behavior. While the processing of emotions from facial expressions had been examined extensively in the behavioral domain, there is little evidence on the neuronal mechanisms involved in the processing of emotions in typically developing preschool children. However, neuronal correlates would permit conclusions about the brain mechanisms relevant for processing socio-emotional stimuli in preschoolers. This, in turn, appears beneficial for gaining an understanding of typical development within this age range. **Consequently, the first objective of this dissertation was to comprehend the normative socio-emotional development of preschoolers, with a particular emphasis on emotion recognition, which was addressed in all three studies**. Studies 1 and 2 investigated emotion recognition using neurophysiological (EEG: ERP and FPVS methods) and behavioral indices of typically developing preschoolers. Despite emphasizing on the trainability of socio-emotional competence, Study 3 also provided insights into children's emotion recognition using ERP markers.

We employed EEG methods across studies to examine neurophysiological mechanisms of preschoolers' emotion recognition contrasting happy, angry and neutral facial expressions. In Study 1 and 3, early (indexed by the P1 and N170) and late (measured by the P3) ERP components were reliably elicited with explicit (Study 1: delayed match-to-sample task) and implicit (Study 3: passive face viewing task) emotion recognition tasks. The P1 and P3 components were modulated by facial expressions (see Table 4.1.1 for a summary of results), whereas the N170 component showed no significant emotion effects across studies.

In line with current EEG and behavioral assessment literature (Curtis & Cicchetti, 2011; D'Hondt et al., 2017; Gao & Maurer, 2010; Sonneville et al., 2002), we expected larger responses to happy as compared to angry and neutral faces. This was true for the happy-neutral contrast, however, we did not observe the expected happy-angry effect. In Study 1, we hypothesized, in accordance with adult studies (Campanella et al., 2002), that repeated exposure to a facial expression would reduce brain responses. This pattern was only discernible for the P1 component, in which repeated happy images elicited weaker responses than novel ones. The P3 yielded mixed results: Study 1 revealed greater responses to angry versus neutral features, whereas Study 3 revealed greater responses to happy versus neutral faces.

Study 2 consisted of two FPVS tasks that compared brief facial expression change responses for happy versus angry faces using either full-blown facial expressions as deviant stimuli (maximum intensity task) or progressively increasing facial expression intensity (gradual intensity task). Indeed, preschoolers perceived brief expression changes for happy as well as angry expressions. In accordance with our hypothesis, we observed greater responses to happy versus angry faces during the maximum intensity task but not during the gradual intensity task. Finally, information derived from the time domain showed a processing advantage for happy over angry faces in later processing stages indexed by the C2 and C3 component in the maximum and gradual intensity condition.

In Studies 1 and 2, we employed explicit emotion recognition tasks to measure the reaction times and accuracy rates of children. In Study 1, children simultaneously saw two faces of different facial expression. Children heard a voice-over of an emotion word while faces appeared on screen and had to designate which of the faces matched the voice-over. In Study 2, children viewed a face morph stimulus (facial expression intensity ranging from 20% to 100%) for a maximum of three seconds and indicated whether the face was neutral, happy, or angry. Preschoolers became more accurate and faster to recognize a facial expression when it was portrayed with a higher expression intensity (Study 2). Paralleling the results of the neurophysiological examination, there were processing advantages for happy compared to angry and neutral faces: Preschoolers were able to recognize a happy face faster than an angry face (as shown by Study 1 and 2) as well as to differentiate a happy from an angry face more accurately (Study 2).

Table 4.1.1 Summary of neurophysiological results concerning modulations by facial expressions.

	P1	**N170**	**P3**
Study 1	happy > neutral angry > neutral repeated happy < novel happy	-	angry > happy angry > neutral
Study 3	happy > neutral	-	happy > neutral

	Frequency domain	**C1**	**C2**	**C3**
Study 2 – max-int	happy > angry	-	happy > angry	happy > angry
Study 2 – grad-int	-	-	happy > angry	happy > angry

In addition to examining behavioral and neuronal correlates separately, we also investigated direct associations between these measures. Specifically, links between parental reports or child assessments with significant ERP modulations were tested (Study 1 and 3). However, no direct connection was detected between neuronal and behavioral correlates across studies.

4.1.2 Trainability of Behavioral and Neuronal Variables

The second goal was to elucidate the trainability of socio-emotional competence. There are already studies on classroom-based face-to-face trainings for preschoolers available, but there has been little research on the efficacy of digital trainings for the home environment. Digital trainings, in contrast to classroom-based trainings, could offer greater flexibility in terms of usage (e.g., when and where to practice) and be tailored to the child's specific needs. In addition, neurophysiological measures are so far rarely included in the evaluation of socio-emotional competence training targeting preschoolers. **Therefore we conducted Study 3 to address the trainability of socio-emotional competence with the digital training Zirkus Empathico examining both behavioral and neuronal correlates.** Children practiced for six weeks with the digital socio-emotional competence training Zirkus Empathico, while the active control group utilized a digital training to learn English. Child evaluations and parental feedback were collected at baseline and immediately following the training. A post-training EEG was obtained. At a three-month follow-up, parental reports were re-collected. The study revealed behavioral and neuronal improvements in the training group.

When comparing pre- and post training parental reports and child assessments, preschoolers in the training group showed significantly larger increases in socio-emotional competence compared to the control group. Specifically, parents of children in the training group reported greater increases in their children's empathy and prosocial behavior than parents of children in the control group. In addition, the training group demonstrated greater improvement in emotion recognition than the control group. Finally, children's problem behaviors decreased significantly more in the training group than in the control group. Concerning the three-month follow-up, parental reports of their children's gain in empathy were higher for the training as compared to the control group.

In addition to parental reports and child assessments, EEG was collected while children observed different facial expressions within a passive face viewing task. Regarding training-related modulations, differences were detected solely for late processing indexed by changes in the P3 component. The training group exhibited larger brain responses to happy faces than to angry or neutral expressions, whereas the control group did not.

4.2 Implications for Preschoolers' Normative Socio-Emotional Development

We investigated the normative socio-emotional competence development of preschoolers using behavioral and neuronal measures across all studies. We focused the neuronal evaluation on emotion recognition from facial expression as the foundation for more complex aspects of socio-emotional competence, such as empathy and prosocial behavior.

4.2.1 Positivity Bias in Preschoolers' Facial Expression Perception

In line with previous research employing emotion labeling, sorting and matching tasks in young children (Bayet & Nelson, 2019; Gao & Maurer, 2010; Sonneville et al., 2002), happy faces were recognized most accurately and fastest within the studies of this dissertation. While previous research focused predominantly on behavioral measures to determine the emotional maturity of preschoolers, the present study also mapped neuronal processes: Overall, positive facial expressions elicited larger brain responses than negative or neutral facial expressions. Consequently, neuronal and behavioral findings point to a positivity bias, a processing advantage for positive versus negative stimuli (Kauschke et al., 2019).

The observed bias among preschoolers contrasts with the preceding neonatal stage. Infant studies detected greater brain activity for fearful, primarily negative features, indicating a negativity bias (see Bayet & Nelson, 2019 for review). Infancy appears to be the onset of fear learning (Leppänen & Nelson, 2012; Xie et al., 2019), with neonates being more attuned to and influenced by negative as opposed to positive aspects of their surroundings (Kauschke et al., 2019). In contrast, identification of happiness appears to be a critical emotion for social bonding during the preschool years. Positive affect seems to facilitate peer acceptance and interaction as well as friendship formation (Denham, 2019). From an evolutionary perspective, prioritizing and searching out positive information may provide greater protection against potentially threatening environmental factors (Kauschke et al., 2019; Lagattuta & Kramer, 2017). Therefore, it seems highly adaptative to detect the emotion happiness early in childhood. Despite mixed findings (Kauschke et al., 2019), the negativity bias was reported to return later in life with increased brain activity for predominantly threat-related facial expressions (e.g., fearful and angry; see Schindler & Bublatzky, 2020 for review). Positive or negative information processing biases thus appear to be dynamic across the lifespan (Kauschke et al., 2019). Particularly during infancy and early childhood, these biases may reflect development-relevant tasks (e.g., learning to avoid threat-related situations; obtaining peer acceptance) required for a typical socio-emotional development. The maturation of brain regions may also play a role in explaining age-related processing differences. As mentioned in the introduction (see chapter 1.2.3), EEG measures are primarily sensitive to the activity of cortical structures. Nonetheless, a direct connection between the amygdala as a subcortical structure and visual cortical regions may contribute to increased facial expression activity (Eimer et al., 2003; Vuilleumier & Pourtois, 2007). Therefore, research indicates that maturational changes in amygdala-cortical connectivity contribute to the differentially biased processing of positive and negative expressions across age groups (Hoehl et al., 2010). **Together, the behavioral and neuronal findings of this dissertation imply that a positivity bias may be a component of typical preschool development.**

4.2.2 The Neuronal Time Course of Facial Expression Perception and Category Formation

Our examination of the maturation of early (P1, N170) and late (P3) ERP components allows us to draw additional conclusions regarding the neuronal time course of facial expression processing in preschoolers. In addition, the results of Study 2 can be incorporated to learn more about the formation of emotion categories in preschoolers.

The P1 Component as a Marker of Early Emotion Processing

In Studies 1 and 3, very early neuronal modulations, as measured by P1 amplitude changes, were observed. In addition, the positivity bias within the P1 component was consistently observed throughout our experiments. These results contribute to a heterogeneous body of research in which processing advantages for happy faces have been reported in both childhood

(Batty & Taylor, 2006; Curtis & Cicchetti, 2011; D'Hondt et al., 2017; Rayson et al., 2023) and adulthood (see Schindler & Bublatzky, 2020 for review). The function of the P1 component in emotion processing is a subject of ongoing debate: On the one hand, increases in P1 amplitude may reflect the rapid extraction of emotion- or saliency-related information prior to the completion of more fine-grained perceptual processes (Todd et al., 2008; Vuilleumier & Pourtois, 2007). On the other hand, previous research suggests that the P1 is governed by early visual processing (Bigelow et al., 2022) and attention allocation (Eimer et al., 2002). Specifically for happy faces, a growing body of evidence indicates that the positivity bias may be associated with the salience of the mouth, as teeth are frequently visible when smiling (for review see Calvo & Nummenmaa, 2016). Further, P1 emotion effects are more frequently observed under conditions of high perceptual difficulty (Schindler & Bublatzky, 2020).

We consistently observed a positivity bias in the P1 component using implicit and explicit tasks. Moreover, in all studies, the stimulus' contrast was controlled to minimize effect based on physical properties (Schindler et al., 2021). It has been argued that, for preschoolers, very early processing of facial expressions might be even their major mean to distinguish between different emotions (Batty & Taylor, 2006; Rayson et al., 2023): Processing appears less automated than in adults (Taylor et al., 2001) and configural processing might be still undergoing maturation (Batty & Taylor, 2006; Curtis & Cicchetti, 2011). Accordingly, the P1 component in preschoolers, being adult-like in morphology, may be sensitive to the processing of emotions with a processing advantage for happiness over other emotions.

The N170 Component Indicates Differential Processing Pattern Compared to Adults

The N170 component appears to exhibit an adult-like morphology beginning in early childhood (Batty & Taylor, 2006; Taylor et al., 2001), which can be confirmed by the present dissertation. However, across our studies, N170 amplitudes were not modulated by facial expressions. Our results are in accordance with the majority of previous preschool research (Batty & Taylor, 2006; Dennis et al., 2009; D'Hondt et al., 2017; Todd et al., 2008). Further, former studies did not detect reliable N170 modulations in later childhood (age range 4-12 years; Bigelow et al., 2022), which contrasts the majority of adult studies reporting N170 modulations for the processing of facial expressions (Hinojosa et al., 2015; Schindler & Bublatzky, 2020). Detectable N170 modulations in adults may be the result of more efficient face processing strategies through acquired face expertise, which is still absent in early childhood (Meaux et al., 2014; Taylor et al., 2001).

Specifically, it has been suggested that developmental changes in N170 modulations may be indicative of the transition from featural processing (extracting facial features individually) to configural processing (perceiving the face as a whole entity) of facial emotions (Bigelow et al., 2022). In one ERP study, preschoolers were shown facial expressions with either high spatial information (fine details, such as facial features like the eyes) or low spatial information (global shape, such as the outline of the face; Vlamings et al., 2010). The authors only detected modulations for the N170 component under conditions of high spatial information, which may indicate a dominance for featural processing (Vlamings et al., 2010). Previous behavioral research indicated, however, that the task performance for configural information processing did not vary between young children and adults (Cassia et al., 2009; Durand et al., 2007). Alternative explanations could involve general cognitive factors that influence emotion processing, especially memory limitations. Young children may encode faces in their configuration, but they may not be able to maintain holistic representations of faces for later recognition (Cassia et al., 2009). In contrast, recent evidence from eye-tracking studies suggests that, compared to adults, young children use distinct fixation strategies when gazing at faces, which may result in distinct neuronal activation patterns (Farrell et al., 2023). In fact, the N170 component in young children was reported to be more adult-like in the presentation of only the eyes than in the presentation of the entire face (Taylor et al., 2001).

In addition, previous research has demonstrated that emotional modulation on the N170 occurs less frequently during active task performance because attentional and emotional decoding compete at this processing stage (Schindler & Bublatzky, 2020). Thus, given that within this dissertation face stimuli included both identity and expression information as well as active tasks, this procedure might have led to a high cognitive load, which in turn influenced the sensitivity of the N170 component to emotion processing. Further, it could be argued that, despite the fact that an adult-like morphology is assumed in preschoolers, significant inter-individual differences may result in smaller amplitudes and a more diffuse topographic distribution (Riggins & Scott, 2020). Particularly for young children, the N170 component seems often bifid in morphology, likely reflecting the activity of two neuronal sources that, with age, evolve such that only one is clearly visible in adults (Batty & Taylor, 2006). Thus, developmental variables such as differential processing strategies of facial expressions in preschoolers and task demands may account for our null findings regarding N170 modulations across studies.

Emotion Sensitivity in the P3 Component may be Task-Dependent

Emotion-related modulations in late processing, indexed by the P3, were reliably elicited within our sample of preschoolers. While the P3 component is typically absent in infancy (Riggins & Scott, 2020), this dissertation is among the first to demonstrate the P3 in preschoolers. Similar to studies conducted with adults, both positive and negative emotions elicited greater amplitudes than neutral expressions (Schindler & Bublatzky, 2020). The P3 component demonstrated a complex pattern of amplitude differences between happy and angry faces: In Study 1, amplitudes were larger for angry compared to happy or neutral faces, whereas Study 3 indicated larger responses for happy compared to neutral faces. The P3 component is typically associated with the integration of emotional information with task-related and semantic information (Schindler & Bublatzky, 2020). Accordingly it indicates that the nature of the task is significant for the effects of the P3 component. Consequently, differences in task design across our studies may account for a portion of the disparate emotion modulations (Cohen et al., 2016). The task in Study 1 was an explicit emotion matching task, in which emotion information had to be consciously remembered and compared with the following facial expression. In Study 3, children were required to press a button whenever an ape face appeared on screen. Consequently, emotional information was processed without consciousness. Facial emotion recognition can be also segmented into automatic implicit and explicit facial processing routes (Holland et al., 2021). These routes also seem to underlie different neuronal pathways, where explicit processing is associated with increased response in the prefrontal cortex and implicit processing with subcortical limbic activity (Herba et al., 2006). Particularly for ERP research it has been found that early emotion effects for facial expressions occur irrespective of task-relevance (Itier & Neath-Tavares, 2017), whereas attention to the emotional expression, specifically attention to fear and anger, was consistently associated with increased P3 amplitudes (Schindler & Bublatzky, 2020). Therefore, the P3 in preschoolers seems to be adult-like in morphology and sensitive to emotion processing, but highly dependent on task demands.

Emotion Categories in Preschoolers

In conclusion, our findings imply that a positivity bias in the processing of facial expressions may be a typical developmental pattern during the preschool years. The early neuronal processing of preschoolers can be broken down into two major components: Firstly, since facial expression processing is still undergoing maturation, children seem to rely on very early processes (as mapped by the P1), while configural processing (as mapped by the N170 component) though available in preschool age, seems to be differential in its neuronal pattern as compared to adults. As for later processing, more top-down processing (as mapped by the P3), emotion sensitivity was detected and susceptible to task demands. In the introduction, I discussed the differential emotion theory (Izard, 1971, 2007; chapter 1.1.2) as a source for the experiments presented in this dissertation. Our findings appear to be partially consistent with this theoretical account's predictions: The emotions encoded in facial expressions elicited a neuronal signature that translated to varying brain response intensities (Study 1 & 3). Study 2 extends these findings to the intensity thresholds needed for the perception of different emotions. We detected a linear increase for both positive and negative emotions which was comparable to previous adults studies (Leleu et al., 2018). However, we also discovered a great deal of interindividual variation in the trajectories of facial expression thresholds in preschoolers in Study 2. In the first place, this contributes to the prior argument regarding the variability of the N170 component. Secondly, it illustrates the potential instability of preschoolers' emotion categories: While some children showed a linear increase in perceiving a face with increasing intensity, other children's trajectories indicated "jumping" such as being able to perceive an emotion at 40% expression intensity and then again at 100% expression intensity. Thus, we would not assert, as the differential emotion theory suggests, that infants "lack" certain emotional categories (Izard, 1971, 2007). Rather, it appears that emotional categories exist but are inadequately defined and have hazy boundaries (Durand et al., 2007).

4.2.3 Outlook: Potential of ERPs and FPVS Markers as Diagnostic Tools

This dissertation's initial emphasis was on the normative development of facial expression processing in preschoolers using neuronal markers from EEG assessments. The EEG method is a noninvasive, quick, and objective measure of brain activity (D'Hondt et al., 2017; van der Donck et al., 2020; Vettori et al., 2019) which, due to its easy applicability, is already used in medicine as a diagnostic tool for young children. In a similar vein, our findings suggest that ERPs and FPVS markers have the potential to characterize developmental processes, revealing an overall positivity bias as well as early and late markers of emotion recognition in preschoolers. The indication of an emotion processing bias may be a significant marker for a variety of clinical presentations; for instance, a negative processing bias has been reported in children who have been maltreated (Curtis & Cicchetti, 2011; Pollak et al., 2009). Moreover, it appears that studies of facial emotion perception in children exposed to negative socio-emotional experience primarily adjust the categorical boundaries and thresholds for identifying specific emotional facial expressions (Bayet & Nelson, 2019). A recently published ERP study examined the effect of emotion processing biases as measured by ERPs on state anxiety in preschool children (Rayson et al., 2023). Typically developing preschoolers with processing biases visible at the P1 (both positive and negative biases were detected) showed a decrease in state anxiety over time. The bias was therefore associated with being a protective factor (Lagattuta & Kramer, 2017). This result highlights the importance of the P1 component as a marker of early emotion processing in preschoolers. Secondly, this study ties in with the work of this dissertation, displaying the potential of ERP assessments for examining early aberrant neuronal patterns in typically developing populations. Especially in non-verbal children, EEG would be an option for examining the status quo or alterations in socio-emotional development. To sum up, EEG assessments could ultimately inform prevention and intervention options for young children by detecting abnormal patterns.

4.3 Implications for the Training of Socio-Emotional Competence in Preschoolers

The focus of Study 3 was the trainability of preschoolers' socio-emotional competence, which was evaluated using behavioral and neuronal measures. We utilized the Zirkus Empathico digital socio-emotional competence training, which was originally designed for autistic children (Kirst et al., 2022; Kirst et al., 2015). In line with positive findings from small-scale research with other digital trainings (e.g., Wu & Kim, 2019), our results suggest an increase in socio-emotional competence as measured by emotion recognition, empathy, and prosocial behavior in the Zirkus Empathico group as compared to the control group. Evaluation of neuronal markers following Zirkus Empathico training revealed differences in emotion processing. Particularly late processing was affected, as indicated by modulations in the P3 component. The children of the Zirkus Empathico group were more sensitive to positive facial expressions. Consequently, the results demonstrate the training's potential for wide-scale implementation in the preschool period. As shown by previous studies examining the training's effectiveness with children on the autism spectrum (Kirst et al., 2022), children with higher needs for socio-emotional training may benefit even more from the Zirkus Empathico training (Mondi et al., 2021; Murano et al., 2020). In the following chapter, considerations are made regarding how this training and the training environment could be modified to sustain effects over time. The results are then evaluated in light of the current digital health care landscape in Germany.

4.3.1 Transferability and Durability of Training Contents

Several of the selected parental questionnaires and child assessments revealed improvements in socio-emotional competence immediately after the training. There are several explanations for the variation between measures (see Study 3 for a comprehensive discussion). This section will relate to the difficulty of directly transferring socio-emotional skills from digital training to real-world situations (e.g., Griffith et al., 2020). Further, the results of the 3-month-follow-up indicated a long-term effect for only one of the empathy measures, but not for emotion recognition nor prosocial behavior. This finding is in line with the previous Zirkus Empathico study targeting autistic children (Kirst et al., 2022), which also indicated existence of some long-term effects (emotional awareness and emotion regulation), but not others (empathy and emotion recognition). Meta-analytic evidence suggests that positive effects from (online) interventions are rarely maintained in the long run (e.g., psychotherapy targeting children with depression: Cuijpers et al., 2020; eHealth interventions in adolescents: Champion et al., 2019). Here, I discuss possible modifications for socio-emotional competence trainings, which may support the immediate transfer of the training's content as well as the long-term maintenance of the targeted effects.

Inclusion of Caregivers into the Training as Assisting Tutors

In our training study, parents were instructed to allow their child to interact autonomously with the digital training and to only intervene in the event of technical issues. By establishing a naturalistic interaction with the training within the child's home environment, we were able to demonstrate that stand-alone digital training can improve the socio-emotional competence of preschoolers. Nevertheless, the participation of family members could be an essential resource for achieving long-term training effects. For instance, caregivers are one of the most influential factors in a child's early social development (Denham, 2018). Meta-analytic evidence indicates that interventions with a family member were more effective in enhancing preschoolers' social competence and reducing their challenging behavior (L. Luo et al., 2022). Therefore, simultaneous training with a parent as an assisting tutor could be a crucial mediator for longer-lasting, more sustainable effects. In particular, the Zirkus Empathico training includes a generalization module in which an emotion manikin can be used to exhibit one's own emotions, which could serve as a starting point for a child and a tutor to discuss (own) emotions (Kirst et al., 2022). During this module, the tutor could provide examples of where these emotions are typically observed in the child's environment, creating numerous transfer opportunities to real-world situations (Hong et al., 2017). Therefore, the inclusion of the generalization module would provide a communication context for the reciprocal sharing of emotional experiences with a family member, including not only parents but also siblings and other close caregivers.

In addition, optimal child development requires support for the development of socio-emotional competence across multiple life domains (Murano et al., 2020). Therefore, the Zirkus Empathico training could be implemented in kindergarten, another crucial socialization environment for the child (Egan et al., 2021). A kindergarten or special education teacher could then undertake the tutor's responsibilities. Both of these alternatives would mandate blended care training (Lampert & Tolks, 2020), in which an educator guides a child through the digital training. According to Wu and Kim (2019), the training could take place in both an individual and a group context. In this context, both peers and educators function as opportunities for transfer to daily life.

Adapting the Training Content

The fact that the Zirkus Empathico training is not narrative-based makes the addition of additional modules feasible and simple to implement. Thus, one could argue for the creation of new modules and the expansion of existing ones. For instance, one finding from Study 2 suggested significant fluctuations in preschoolers' recognition of facial expressions of varying intensities, which may be indicative of maturing emotion categories (compared to adult studies, e.g., Leleu et al., 2018). Accordingly, the existing module for emotion recognition could be expanded to include emotions with varying intensities or blended emotions. In addition, modules covering additional aspects of socio-emotional competence could be included (e.g., a previous study of Zirkus Empathico, highlighted the importance of emotion regulation; Kirst et al., 2022). A further expansion could consist of modules that promote tutor-child interactions. There could be, for instance, a "psychoeducation module" aimed at the tutor that provides examples of how to explain aspects of socio-emotional competence in child-friendly language (questions such as "What is empathy?" and "Why are our emotions important?" could be addressed by this module). In addition, the relationship between socio-emotional competence and overall well-being should also be explained and emphasized. On a different note, modules that allow dual use, i.e., joint interaction between the child and a tutor would be helpful (Reid Chassiakos et al., 2016). For example, a classic memory game could be implemented in which the images on the virtual playing cards depict individuals reacting to various situations with various emotions (e.g., a person holding an ice cream cone while smiling). On the one hand, information about emotions can be repeated in a lighthearted manner. On the other hand, socio-emotional competence can be exercised with the tutor throughout the game (e.g., waiting one's turn and regulating oneself when winning or losing).

Modulating the Training Intensity

According to a meta-analysis of classroom-based socio-emotional competence trainings, the duration and intensity of the training played a significant role in sustaining the training effects (Nelson et al., 2003). The duration of our home-based socio-emotional competence training was six weeks, whereas classroom-based socio-emotional competence trainings, which have proven to be effective, typically encompass several months to a year (Wadepohl et al., 2011). Therefore, increasing the length of the training time could improve the sustainability of effects. Given the age of the target audience, we suggested a weekly training session of one hour for Study 3. Therefore, it would be preferable to increase the number of training weeks rather than the weekly time commitment. Comparing classroom-based training with digital training for the development of socio-emotional competence could be the next stage in evaluating the strengths of effects. This study would also contribute to the debate over whether classroom-based or digital trainings are more suitable for fostering the social and emotional development of children. A third condition in which these two approaches are combined is also conceivable in order to determine whether training at home and at the kindergarten facility provides the greatest training success.

4.3.2 Making Digital Socio-Emotional Competence Trainings Available to the Public

There are currently a large number of digital trainings available to the public that frequently lack a scientific basis. This carries the risk that the health care component is not established and that the content is inaccurate or lacking in significance (Lampert & Tolks, 2020). Considering that studies to date have demonstrated the efficacy of the Zirkus Empathico program as a digital socio-emotional competence training for clinical and non-clinical groups, it may be prudent to initiate a broader implementation in order to increase its visibility. The expansion of digital socio-emotional competence trainings within the German health care system would be one opportunity.

The advancing digitalization as well as the unexpected COVID-19 pandemic accelerated the development of digital support services for people with mental health problems (Dramburg et al., 2021; Lampert, 2020). Digital Health Applications (DiGA) may be prescribed to German patients with mental health issues following the passage of the Digital Health Care Act (2019). According to the German Federal Institute for Drugs and Medical Devices (2020), to be a prescribable DiGA, positive health care effects must be demonstrated, e.g., within a randomized controlled trial. DiGAs may reduce health care gaps because they facilitate time- and location-independent accessibility, target-group-specific access to younger (but also difficult-to-reach) groups, and the option to access these services anonymously, which may reduce the fear of stigmatization (Geirhos et al., 2019; Halldorsson et al., 2021; Lampert & Tolks, 2020). The increasing media usage of children and adolescents also enhances the relevance of DiGAs for younger populations (Herodotou, 2018; Lampert, 2020). However, no DiGA has been formally approved for infants or adolescents as of yet. First meta-analyses for digital training and therapy options report small (for depression; Garrido et al., 2019) to medium (for anxiety disorders; Geirhos et al., 2019) effects. As the Zirkus Empathico training has been demonstrated to be effective for autistic children (Kirst et al., 2022), it would be worthwhile to explore options for a DiGA.

One current shortcoming of the DiGA concept, however, is that digital application can only be prescribed to individuals with a confirmed diagnosis (Lampert & Tolks, 2020). Many preschoolers may not yet meet diagnostic criteria for a psychiatric disorder, but they exhibit emergent deficits in socio-emotional competence relative to their peers of the same age (Mondi et al., 2021). Thus, it would be another option to certify the Zirkus Empathico training as a digital prevention tool (e.g., through the "Zentrale Prüfstelle Prävention"). Alternatively, recent conceptualizations request that mental health should be promoted as a continuum from well-being to psychopathology (Mondi et al., 2021). Particularly relevant would be socio-emotional competence trainings, which strengthen skills (such as recognizing and modulating emotions) that serve as protective factors against problem behaviors (Alwaely et al., 2021; Colomeischi et al., 2022). If this conceptualization were to be adapted to the German health care system, it would be essential to include prevention programs in the DiGa approach. In oth cases, our study could serve as a template for a large-scale prevention study to demonstrate the efficacy of the Zirkus Empathico training.

Challenges of Distributing Digital Trainings

Even though the Zirkus Empathico training could be certified as a DiGA or official prevention program, this does not necessarily imply that it is inherently accepted and utilized by the general public. Educational digital trainings compete with a large number of engaging alternatives, making it especially difficult for preventive or health-promoting offerings to attract users' attention (Lampert, 2020; Lampert & Tolks, 2020). In addition, for preschool children, it should be considered that it is mostly the caregivers who decide which apps are used by their child. Caregiver (parents or kindergarten instructors) and stakeholder (e.g., pediatricians) concerns may be raised by the unique digital delivery of the training. Additionally, even a high-quality, empirically-based, and well-designed digital application does not guarantee that the intended health-promoting objectives will be achieved (Geirhos et al., 2019; Murano et al., 2020). Therefore, there should be a transparent expectation management regarding the effectiveness of the training and usage guidelines. The digital training of socio-emotional competence can provide families with incentives to engage in actions that foster, for example, more empathic or prosocial behavior. However, the influence of the training must be understood in the context of the family's ability to provide the child with transfer opportunities into his or her daily life (e.g., communication opportunities about own emotions in the family context). To encourage responsible media consumption, clear weekly utilization recommendations (e.g., one hour per week; see next paragraph on "Responsible Media Consumption") should be provided. To effectively and responsibly disseminate the training, an implementation strategy must be in place. It would be essential to collaborate with institutions that are pertinent to families, such as kindergartens and pediatricians, to promote and communicate the benefits of the training.

Responsible Media Consumption

The Zirkus Empathico training is constructed as a serious game to promote socio-emotional competencies with clear educational goals and entertainment elements (Hollis et al., 2017; Lampert & Tolks, 2020). Gamification, the inclusion of game-design principles (Lampert, 2020), is an integral part of the training to enhance motivation (Kirst et al., 2015). Furthermore, the training contains theme-based and partly immersive and naturalistic video content, an engaging reward system (Fletcher-Watson et al., 2019), and the provision of choice (e.g., free selection of open modules and tasks; Whyte et al., 2015). Indeed, the largest evidence of generalized learning was reported for interventions with the greatest number of serious game elements (see Whyte et al., 2015 for review). However, entertaining elements of digital trainings carry risks: First, an obsession with gaining rewards and receiving constant gratifications can interfere with the comprehension of the actual training material (Lampert & Tolks, 2020). In addition, the digital training mode is frequently set to auto-advance in order to maximize the duration of engagement, without taking into account the fact that the child may need time to comprehend the presented content. These factors may result in a failure to satisfy the training's learning objectives and an increase in training duration. In addition, the "addictive potential" of digital training may result in the child's isolation as they are drawn into the digital world (Reid Chassiakos et al., 2016), or to conflicts between the caretaker and the child, if digital training usage must be restricted (Hadlington et al., 2019). Previous research also indicated that exceeding screen time for preschoolers was related to increased behavior problems (McArthur et al., 2022). Therefore, in order to assist caregivers in implementing the digital training, digital training for young children must be accompanied by information about responsible media consumption. It would be beneficial to provide information on recommended use per day (e.g., recommended screen time for preschoolers is no more than one hour per day; McArthur et al., 2022) as well as an outline for a media usage plan which guides caregivers to monitor and control for excessive use (Reid Chassiakos et al., 2016). The design of the digital training could also actively support caregivers in setting time boundaries for the child. The Zirkus Empathico training could for example actively prompt to take a break and motivate to engage in other activities (Reid Chassiakos et al., 2016). In addition, a fixed time could be agreed upon in advance with the caregiver and plainly displayed on the display, so that expectation management regarding the time spent with the training is defined from the start. Lastly, data protection needs to be handled carefully to protect the child and to reduce concerns of caregivers about the usage of the digital training.

4.4 Directions for Future Studies

The previous chapters discussed implications from our studies for the maturity and trainability of socio-emotional competence in preschoolers. This following section discusses ways to enhance future research on this topic.

4.4.1 Multidimensional Assessment of Children's Development

Future studies would benefit from a multidimensional assessment that investigates not only the maturity of children's socio-emotional competence, but also includes aspects of their cognitive (Bell & Wolfe, 2004; Bell et al., 2019), language development (Ruba & Repacholi, 2020; Salmon et al., 2016) as well as the environment they live in (Beauchamp & Anderson, 2010).

Considering Cognitive Factors

Socio-emotional competence is frequently referred to as "non-cognitive" in both research and practice (Mondi et al., 2021). However, numerous researchers have argued that this label is incorrect, as socio-emotional competence is frequently rooted in cognitive skills (Bell & Wolfe, 2004). This dissertation examined the development of emotion recognition as a facet of socio-emotional competence using behavioral and neuronal markers. Children's attention allocation skills have been hypothesized as a cognitive factor that may explain differences in emotion recognition (Bell et al., 2019). The allocation of attentional resources is believed to be a function of facial expression processing (Schindler & Bublatzky, 2020), as indicated by studies involving children with Attention Deficit Hyperactivity Disorder (ADHD). The poorer performance of children with ADHD compared to typically developing children on facial emotion recognition tasks may be a result of their inattention to salient facial cues during encoding (Ansari Nasab et al., 2022; Da Fonseca et al., 2009). Another cognitive factor that has been discussed to explain differences in emotion recognition is the working memory of a child (Bell et al., 2019). A recently published theory suggests that affective information occupies our limited working memory resources more readily (van Dillen & Hofmann, 2023). Attention to affective stimuli, and the subsequent processing of these stimuli, may thus depend critically on the availability of working memory resources. Accordingly, the investigation of this triad, namely, attention, emotion processing, and working memory, could provide important insights for the development of emotion recognition in preschoolers. Within this dissertation, we included information about cognitive abilities as covariates (e.g., see Study 1; children's short-term memory) to partial out cognitive effects related to cognitive load. Given that Study 1 included an EEG task which demanded many cognitive resources from the children (i.e., decode an emotion, store the information about the emotion and decide whether it is the same as the next emotion is presented), our study would have profited from examining attention and working memory within this context. Differences in emotion processing could have been compared and contrasted to differences in children's cognitive level (e.g., Do children with lower working memory indeed show differences in neuronal signal to repetition of facial expressions?).

Assessing Language Proficiency

In the context of socio-emotional development, language is also significant because it is essential for expressing and moderating emotions, and thus for fostering social relationships (Bigelow et al., 2022; Ruba & Repacholi, 2020). Children who have not achieved age-appropriate language proficiency are at increased risk of difficulty in language-related cognitive and socio-emotional tasks (Salmon et al., 2016). Particularly for emotion processing, language plays a detrimental role in children's ability to process facial expressions as it represents the mean to construct emotion categories (Bigelow et al., 2022; Ruba & Repacholi, 2020). Emotion words in turn influence how facial expressions are encoded and remembered, as previous studies showed that the inclusion of emotion labels in emotion categorization tasks improves children's and adults' performance (Calvo & Nummenmaa, 2016). Therefore, broad language abilities as well as knowledge about emotion words should be included in future research on children's emotion recognition development.

Deriving Information of the Child's Context

In the evaluation of the training's success, variables pertinent to the child's social development may be considered (e.g., family structure; Beauchamp & Anderson, 2010). Beneficial would be, for example, the influence of sibling interactions. According to previous research, not the quantity of siblings, but the quality of their relationships may have a positive effect on the socio-emotional development (Yucel & Yuan, 2015). Examining whether the quality of interactions between siblings can be modulated by the training may help to understand more about how a digital training changes family interactions (e.g., discussing emotions within the family). Further, if a future study employs a caregiver as a training tutor, one could examine as training mediators the impact of the caregiver's personality traits (Ruiz Ortiz & Barnes, 2019), emotion socialization style (Ornaghi et al., 2019), or socio-emotional competence (Huhtala et al., 2014). In addition to parental questionnaires and child assessments, future studies should also include observer-based assessments to counteract the bias of subjective ratings as well as ratings of other caregivers (e.g., kindergarten teachers).

4.4.2 Adaptions to EEG Assessments of Emotion Recognition

This dissertation assumed that emotion recognition is the foundation for more complex aspects of socio-emotional competence, including empathy and prosocial behavior. We utilized a variety of paradigms to evaluate emotion recognition using EEG. Future research would benefit from testing different stimuli and expanding their scope to examine the association of emotion recognition with emotion regulation:

Choice of Stimuli

Within the EEG paradigms angry, happy and neutral facial expressions were examined in the context of normative emotion recognition development. As the majority of neuroscientific studies for younger populations barely covers the basic emotions (happiness, anger, fear, sadness, surprise; Castro et al., 2016), future research could be expanded to include facial expressions of these emotions to obtain a deeper understanding of neuronal processing differences. For instance, it would be worthwhile to integrate the emotion fear, which, like anger, indicates the presence of a threat. But conceptually, anger presents a greater direct threat that may elicit avoidance, whereas fear elicits prolonged threat responses because it signals that something in the environment could be threatening and that it would be necessary to provide information about the potential source of the threat (Leppänen & Nelson, 2012). Specifically, the incorporation into the FPVS method would aid in answering the question of whether fearful or furious facial expressions are detected faster, i.e. with less emotion intensity (Leleu et al., 2018).

Further, we employed facial expressions of adults which were unfamiliar to the children. However, within the preschool period, children may be most familiar with facial expressions of their caregiver(s) or children which they encounter regularly in kindergarten facilities (e.g., one study reported decreased N170 amplitudes for faces of strangers as compared to faces of preschoolers' mothers; Kungl et al., 2017). Thus, replicating these experiments with facial stimuli that are more relevant to the child (e.g., facial expressions of the mother) may reveal, as has already been demonstrated in adult studies, differential neuronal facial expression processing in children (e.g., Bayer et al., 2021).

Emotion Regulation as an Additional Facet of Socio-Emotional Competence

This dissertation provided first evidence that ERP modulations were observed after completing the digital socio-emotional training Zirkus Empathico. In the training group, we detected differences in later processing, as indicated by greater P3 amplitudes for happy vs. neutral faces, but not in the control group. As discussed in a previous chapter (see section 4.2.1), this positivity bias may be a protective factor (Lagattuta & Kramer, 2017; Tugade & Fredrickson, 2007). Therefore, this effect could be interpreted as preschoolers experiencing a fine-tuning of their perceptual learning toward a beneficial processing style (Bayet & Nelson, 2019; Pollak et al., 2009). As a consequence, more neuronal resources may be focused on happy facial expressions. Further, previous research linked the P3 to emotion regulation processes (Hajcak et al., 2010). Therefore, the Zirkus Empathico training may also result in reorientation processes toward positive emotional states, which has been identified as an effective emotion regulation strategy (Tugade & Fredrickson, 2007). Thus, as indicated by these neuronal findings as well as previous research with the Zirkus Empathico training (Kirst et al., 2022), emotion regulation may be another facet of socio-emotional competence which should be considered in future studies.

Emotion recognition and emotion regulation are substantially related but difficult to empirically and theoretically distinguish from one another (Morales & Fox, 2019; Ornaghi et al., 2019). One reason is that as soon as we perceive an emotion, our body reacts reflexively and may regulate our systems without our conscious input. A definition by Eisenberg & Spinrad (2013) describes emotion regulation as the capacity to productively modulate, inhibit, and enhance emotional experiences and expressions, and to manage them in a way that is appropriate to the social context. According to this definitions, emotions can be willfully controlled and modulated at various stages of the emotion generative process. In previous EEG research on children, goal-directed emotion regulation tasks such as the cognitive reappraisal task were utilized (see Kennedy & Montreuil, 2020 for review). Reappraisal involves changing the emotion meaning and significance of an emotion-inducing stimulus (Krompinger et al., 2008). In adult samples, a number of researchers have shown that LPP amplitudes are reduced when participants are instructed to reappraise unpleasant stimuli (Krompinger et al., 2008). There is also growing evidence that the late positive potential (LPP, after 600 ms) may be a reliable neuronal indicator of children's cognitive reappraisal abilities (Kennedy & Montreuil, 2020). For example, previous studies found reappraisal-induced reductions in LPPs in children as young as 5 years old (Myruski et al., 2019). Preschoolers' prosocial behavior was also associated with LPP responses to painful stimuli (Decety et al., 2018). Collectively, a future experimental setup should incorporate a task examining emotion regulation (e.g., a cognitive reappraisal task). Further, parental questionnaires (e.g., Emotion Regulation Checklist; Shields & Cicchetti, 1997) and child assessments of emotion regulation (e.g., Incredible Cake Kids task; Grabell et al., 2019) could be included.

4.4.3 Linking Neuronal and Behavioral Correlates of Socio-Emotional Competence

Despite what many theoretical models suggest (e.g., Hoffman, 2000), social-emotional development is not necessarily linear (Beauchamp & Anderson, 2010). For example, when children encounter novel learning experiences (e.g., through a training) or are exposed to highly stressful situations, there may be reorganizations in the brain (e.g., children who have experienced maltreatment are more sensitive to negative stimuli, Pollak et al., 2009) as well as observable improvements or regressions in behavior (Thomasgard & Metz, 2004). Some neuronal changes may not necessarily be associated with any apparent changes in behavior at this stage of development (Parker & Nelson, 2005), but they may become visible in later childhood. This factor may contribute to our null findings concerning associations between neuronal and behavioral measures in our preschool sample across our studies. To depict the described complexity appropriately, it would be of value to use a longitudinal framework in which the same children are assessed regarding changes in socio-emotional competence across their development. Further, we observed substantial interindividual differences in our neuronal measurements (e.g., see Study 2). It might therefore be advantageous to subdivide every age range into smaller steps (e.g., in the case of preschool period to compare 4-year-olds to 5-year olds, following 5-year-olds to 6-year-olds and so forth; Riggins & Scott, 2020) and to integrate ERP measures at all time points to track the neuronal trajectories. For this approach, it would be important to account for task difficulty both in behavioral and neuronal assessments in every age group to achieve comparable results (Herba et al., 2006; Johnston et al., 2011).

Further, behavioral and neuronal correlates may represent multifaceted processes, not all of which are inherently attributable to a single aspect of socio-emotional competence (Beauchamp & Anderson, 2010). For example, questionnaires assessing empathy development might in part include questions on prosocial behavior (see Study 3 for a detailed discussion). Similar challenges arise for EEG assessments: In this dissertation, we focused primarily on the acquisition of neuronal correlates associated with emotion recognition. EEG assessments were carried out within a highly-controlled and laboratory-based setting, employing strongly prototypical, high-intensity facial expressions to minimize confounding variables. However, even in this context, emotion recognition and processing are not independent of other processes (Beauchamp & Anderson, 2010), i.e., during emotion recognition, regulatory processes are also active, impacting neuronal activity (Morales & Fox, 2019). Therefore, it seems necessary to examine each facet of socio-emotional competence in greater detail. Using emotion recognition as an example, it would be beneficial to follow the suggested multidimensional assessment (see chapter 4.4.1) to account for not only the different processes that are active during emotion recognition that are directly related to the construct (e.g., emotion regulation), but also other factors (e.g., cognitive skills) in order to gain a better understanding of the relationships between neuronal and behavioral correlates as well as the influence of development.

4.5 Lessons Learnt for Approaching Developmental Research

This dissertation makes several contributions to the development of preschoolers' socio-emotional competence. In this final chapter, I derive general implications for my work in the field of developmental neuroscience for the topics of ecological validity, view on strengths vs. deficits as well as Open Science practices.

4.5.1 The 'Real-World' Dilemma

The generalizability of my findings, i.e., the extent to which my primarily laboratory-based experiments permit the generalization of results beyond the laboratory setting (Holleman et al., 2020), was one of the aspects of my research that concerned me, especially when assessing socio-emotional competence. As an example, I asked parents to rate their child's behavior (e.g., "Do you perceive your child as more prosocial after the training?"). But how well do these ratings reflect the actual behavior of the child (e.g., Did the child show more prosocial behavior in social interactions after the training?")? Another example for challenges in generalizability can be drawn examining the neuronal correlates of children's emotion recognition with EEG. The EEG data from all of my studies were collected under highly-controlled laboratory conditions, which is rather distant from preschoolers' typical environments. Previously, it was criticized that laboratory tasks might underestimate children's facial processing abilities and that it is unknown how this performance can be generalized to facial expression processing in everyday life (McKone et al., 2012). In addition, static, grayscale, and highly stereotypical facial expression stimuli were used in my studies, which is not necessarily comparable to real-world encounters characterized by rapid changes and a range of emotions (Schneider et al., 2022). However, this procedure was chosen deliberately to minimize confounding variables and attribute effects as plainly as possible to children's performance in emotion recognition. If I were to observe children in their real-life environment (e.g., reactiong to their caregivers' facial expressions), I might experience different and more naturalistic responses. Nonetheless, it would be more challenging to determine whether this behavior was solely attributable to my variables of interest, which may impact the generalizability of my findings. This example highlights the trade-off between environmental control and behavior of interest in the actual world as defining factors of ecological validity (Hacker et al., 2009; Holleman et al., 2020; Matusz et al., 2019). Knowing which behavior I wish to investigate in which context can greatly facilitate the conception of a study design and the selection of measures. Together with other developmental researchers, I developed the Multidimensional Assessment of Research in Context (MARC) tool to assess the degree of ecological validity within a study to ultimately create more awareness for this aspect of a study (Naumann, Byrne, et al., 2022).

A Tool to Assess the Ecological Validity of Your Study

The MARC tool is based on the idea that phenomena can be studied with different approaches (or contexts), from using highly controlled tasks to real-world research designs (Naumann, Byrne, et al., 2022). These approaches have recently been integrated within a cyclical framework, composed of three "nodes" which are the (1) controlled laboratory approach, (2) partially naturalistic laboratory approach, and the (3) naturalistic real-world research approach (Matusz et al., 2019). It should be emphasized that, within this framework, laboratory research is neither superior nor inferior to "real-world" approaches, and that all three nodes are vital to the development of more ecologically valid research. As first step within the MARC tool, the researcher can describe the behavior they intend to observe and the context they intend to generalize. The instrument then poses seven queries regarding the characteristics of the study: sample, testing site, task, stimuli, measures, non-research stakeholders, and a (potential) intervention component. Each of these questions can be answered on a three-point scale linked to each of the three approaches: controlled laboratory-based, partially naturalistic, and naturalistic real-world. The output of the MARC tool is a summary of the questions and a compass plot, reflecting the level(s) of the study's ecological validity. Consequently, this tool may assist researchers in striking a compromise between the realism with which a behavior can be measured and the minimization of environmental influences. The MARC tool and its corresponding source code are freely available for use (https://marcweb.herokuapp.com/).

4.5.2 Change the Narrative: Emphasize Strength Promotion Rather Than Deficit Reduction

My dissertation examined the trainability of socio-emotional competence in typically developing preschoolers. A vast number of research within this field has focused on "deficit-reducing" interventions (Mondi et al., 2021). Further, measures within these studies often use symptom reduction as the main outcome for training success (e.g., Burnham Riosa et al., 2017 for studies with autistic populations). Obviously, such interventions are essential for serving (sub)clinical populations. Nonetheless, it also implies that assistance should only be provided when clinically significant symptoms are present. In addition, parents are frequently hesitant to utilize support services for their child's aberrant socio-emotional behavior out of fear of stigmatization and lack of approval that their child "deviates from the norm" (Halle & Darling-Churchill, 2016).

In contrast to this line of research, the purpose of this dissertation was to investigate a training suitable for all children that focuses on enhancing their socio-emotional competence, which can have a positive impact on their well-being (Beauchamp & Anderson, 2010; Beelman, 2019). This training is open and recommended for all preschoolers, regardless of their socio-emotional development, and can reduce stigma and normalize help-seeking behavior by making it accessible to all children (Halldorsson et al., 2021). In addition, measures such as the Strength and Difficulties Questionnaire (SDQ, Goodman, 1997) were included that considered both a child's strengths and weaknesses. This procedure aligns with other strengths-focused approaches which prioritize and measure a child's competence development and individual resources after he or she received a training or therapy (see Sydow et al., 2013 for meta-analysis).

For the examination of neuronal measures, the concept of *neurodiversity*, which originated in the field of neurodevelopmental disorders such as autism, should also be highlighted (Dwyer, 2022). Neurodiversity asserts that some characteristics typically characterized as deficient are, in fact, merely atypical due to a particular neurological wiring. Consequently, it is simply a difference that should be respected as any other human characteristic (e.g., race, gender; Dwyer, 2022). A distinct neuronal pattern as measured by ERP or FPVS markers may therefore not be interpreted as a deficiency, especially in the context of developmental research where maturation is still in progress.

4.5.3 Why Open Science Matters in (Developmental) Research

As evidenced by the emergent replication crisis in psychological research, a significant proportion of the literature may contain false or misleading evidence (Ioannidis, 2005; Klein et al., 2018). *Transparency and Openness Promotion* (TOP) guidelines were therefore established and endorsed by researchers, institutions, funders, and scientific journals in an effort to provide reproducible, reusable, replicable, and openly accessible research practices (Nosek et al., 2015; Nosek et al., 2022). Developmental research has adopted open science practices more slowly than other disciplines, in part because the majority of developmental research is descriptive or exploratory (Gennetian et al., 2022). In addition, developmental studies frequently have low statistical power because of the small sample sizes that result from the costs and difficulties of recruiting and studying minors (Gennetian et al., 2022). In order to facilitate an open discussion about my research, it has been advantageous for me to adapt the TOP guidelines in as many ways as feasible. Prior to data collection, I adhered to a hypothesis-testing approach using pre-registered study designs (e.g., objectives and methods of Study 3). Particularly, the pre-registration procedure enabled me to carefully consider what and how I wanted to conduct my research, which can save time and money in the long run. This appears to be even more important in developmental science than in other subfields, as children are a vulnerable population with significant societal significance. Moreover, the substantial financial and time investments required to study children's development impose an ethical obligation on researchers to maximize research quality, including adherence to the TOP guidelines (Gennetian et al., 2022). In addition, all of the studies conducted for this dissertation were made available as preprints prior to publication and have a corresponding online repository with freely accessible analysis scripts and data files, which facilitates the detection and correction of any inadvertent analysis pipeline errors (Klein et al., 2018). This aspect of my work facilitated clear communication with my collaborators, which ultimately improved and bolstered my research management practices.

I am aware that my research practices are not yet fully adherent to the TOP guidelines. But the adoption of open science is not an all-or-nothing proposition (Klein et al., 2018; Nosek et al., 2015), and every step toward a less error-prone, reproducible research workflow contributes to the developmental science community. Contributing to the advancement of open science, I aspire to serve as a role model for the next generation, particularly in the fields of developmental neuroscience and psychology.

4.6 Conclusion

The objectives of this dissertation concerned the social-emotional development of preschoolers, particularly (1) the maturity and (2) the trainability of their social-emotional competence. With regard to the first objective, the focus was on the fundamental socio-emotional competence emotion recognition. Employing both behavioral and neuronal measures, we detected a processing bias toward happy faces as a potential marker of preschoolers' typical emotion recognition development. Thus, happiness seems to be the most readily processed within this age range and may therefore be a significant contributor to socialization processes (e.g., formation of friendships). Time and frequency domain information consistently indicated modulations by emotions. Larger brain signals were detected for emotions at a higher intensity. However, the results exhibited substantial inter-individual variation. Thus, categories for fundamental emotions appear to exist in preschoolers, but due to continuous maturation, they may not be as stable as they are in adults.

Regarding the trainability of socio-emotional competence in preschoolers, both behavioral and neuronal measures revealed encouraging results. Parental and child assessments revealed increases in both fundamental (emotion recognition) and more complex socio-emotional competence (prosocial behavior). In addition, late neuronal processing indicated that the training group was attentive to positive stimuli, which may be a useful regulatory strategy. As functional socio-emotional competence is an essential factor in lifelong well-being, these findings underscore the need to implement digital socio-emotional trainings within the German healthcare system (e.g., as a digital health application or prevention program). As for future research, I propose investigating these topics considering a multidimensional perspective, incorporating language and cognitive correlates as well as other aspects of socio-emotional competence (e.g., emotion regulation), in order to support the generalizability and robustness of these findings and to extend the knowledge gained in this dissertation.

Glossary of Terminology

Empathic concern	Tendency to react with feelings of sympathy and concern for unfortunate others.
Empathy	Ability to share and understand the emotional states of another person, with the recognition that the other is the source of one's state.
Emotion recognition	Awareness that an emotion has been expressed and the labeling of facial expressions.
Emotion regulation	Capacity to productively modulate, inhibit, and enhance emotional experiences and expressions, and to manage them in a way that is appropriate to the social context
Prosocial behavior	Positive interactions with other people, such as assisting, sharing, cooperating, and comforting, which have a positive impact on social relationships.
Socio-emotional competence	Comprehension, expression, and regulation of our own and others' emotions, thoughts, and behaviors, as well as our responses.

List of Abbreviations

ACC	Anterior cingulate cortex
ADHD	Attention Deficit Hyperactivity Disorder
AIC	Anterior insular cortex
BCA	Baseline-corrected amplitude
CC	Complete case
CMM	Columbia Mental Maturity Scale
CPM	Coloured Progressive Matrices
DiGA	Digital Health Applications
DLPFC	Dorsolateral prefrontal cortex
DRKS	German Clinical Trials Register
EEG	Electroencephalography
EMK 3-6	Inventory to survey of emotional competences for three- to six-year-olds
EMT	Emotion matching task
ERP	Event-related potential
ERT	Emotion recognition task
FDR	False discovery rate
fMRI	Functional magnetic resonance imaging
FPVS	Fast periodic visual stimulation
GEM	Griffith Empathy Measure
GLMM	General linear mixed model
ICA	Independent component analysis
IFG	Inferior frontal gyrus
ISI	Inter-stimulus interval
ITI	Inter-trial interval
ITT	Intention-to-treat
LMM	Linear mixed model
MARC	Multidimensional Assessment of Research in Context
PDI	Physical dissimilarity index
PP	Per-protocol
PPVT-4	Peabody Picture Vocabulary Test the 4th Edition
ROI	Region of interest
RCT	Randomized controlled trial
RT	Reaction time
SCQ	Social Communication Questionnaire
SDQ	Strength and Difficulties Questionnaire
SES	Socioeconomic status
SEC	Socio-emotional competence
SNR	Signal-to-noise ratio
SRS	Social Responsiveness Scale
SSVEP	Steady-state visual evoked potential
STM	Short-term memory
STS	Superior temporal sulcus

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Ich erkläre hiermit an Eides statt, dass ich die vorliegende Dissertation selbständig verfasst, mich außer der angegebenen keiner weiteren Hilfsmittel bedient und alle Erkenntnisse, die aus dem Schrifttum ganz oder annähernd übernommen sind, als solche kenntlich gemacht und nach ihrer Herkunft unter Bezeichnung der Fundstelle einzeln nachgewiesen habe. Ich erkläre des Weiteren, dass die hier vorgelegte Dissertation nicht in gleicher oder in ähnlicher Form bei einer anderen Stelle zur Erlangung eines akademischen Grades eingereicht wurde.

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