University of Helsinki
Faculty of Arts
Master's Programme in Cognitive Science

Empathy and EDA Synchrony in Virtual Reality Collaboration

Master's Thesis

May 10, 2022

Hanna Ylätalo

Author:	Hanna Ylätalo
Title of thesis:	Empathy and EDA Synchrony in Virtual Reality Collaboration
Date:	May 10, 2022
Pages:	45
Major:	Cognitive Science
Supervisor:	Riikka Möttönen
Instructor:	Silja Martikainen, Ben Cowley (Department of Modern Languages)

Objective. Empathy is essential for successful collaboration. Empathic mechanisms partly rely on receiving sensory socioemotional information during social interactions, such as facial expressions. Today, computer-mediated communication (CMC) covers a large part of daily social environments. However, socioemotional information during CMC is restricted, which directly impacts social processes and therefore, different empathic skills may become beneficial in CMC environments compared to face-to-face interactions. The impacts of CMC on social processes are insufficiently understood and studies provide mixed results. Physiological synchrony is a useful tool to study underlying aspects of social interactions. In psychophysiology, physiological states can be evaluated according to physiological responses, such as changes in electrodermal activity (EDA), which is a measure of sympathic nervous system activity. EDA synchrony is connected to empathy and collaboration in several studies. The purpose of this study is to reveal connections between empathic skills, collaborative task performance and EDA synchrony in CMC environment.

Methods. EDA signals of twenty-nine pairs were recorded during collaborative task performance in VR environment. Participants were unfamiliar with each other and could not see each other during performance. Before the experiment, they conducted two empathy tests: Interpersonal Reactivity Index (IRI) and Reading the Mind in the Eyes (RME). The performance was measured and connected with empathic abilities using statistical methods. EDA synchrony indices were calculated for each pair, and were statistically connected with empathy and task performance.

Results and Conclusions. The results surprisingly showed that IRI subscale 'personal distress' predicts collaborative task performance in VR environment. Personal distress reflects emotional sensitivity and is conneceted to social avoidance and maladaptive emotion regulation strategies. This result indicates that different social skills become beneficial in CMC environment, where participants cannot see each other, as in face-to-face collaboration. In addition, RME, which reflect skills in complex emotion recognition, was connected to performance on a trend level, which is supported by previous findings. EDA synchrony occured, but was not connected with either empathic skills or collaboration.

Keywords: empathy, CMC, collaboration, physiological synchrony

Language: English

Contents

Foreword

The data used in this thesis is collected by part of HUMEX -project of Cognitive Brain Research Unit in University of Helsinki.

I would like to give special thanks for my supervisors Silja Martikainen and Benjamin Cowley for guidance throughout the process, and Tommi Makkonen for much appreciated help with signal processing and analysis.

1 Introduction

Throughout evolutionary history, human social abilities have evolved to support face-to-face interaction. However, the rapid digitalization during the past decades has changed daily social environments enormously, which impacts natural human social processes. Computer-mediated communication (CMC) platforms offer novel tools for self-expression and interaction, yet CMC differs from face-to-face interactions in several ways, which directly impact the quality and dynamics of social interactions (Liu et al., 2019; Järvelä et al., 2019). Human empathy and collaboration are social abilities which facilitate everyday social wellbeing and functioning society. Although CMC covers a large part of daily social interactions, its impact on these emergent social processes remains insufficiently understood. A range of study exists, yet a comprehensive theory is still missing. Without detailed understanding of how these processes emerge, it is hard to design technology to support empathic and collaborative actions.

Empathy is a set of skills that enable smooth interaction. Empathic abilities support bonding, mutual understanding, and engagement in social situations (Chartrand and Bargh, 1999; Decety and Jackson, 2004; Lakin and Chartrand, 2003). Empathic mechanisms transfer embodied states between individuals and emergence of empathy partly relies on receiving sensory information of others' behavior and emotional states (Kret, 2015). However, embodied, socioemotional communication is restricted in CMC environments, and studies indicate that empathic mechanisms function differently during CMC compared to face-to-face interaction (Carrier et al., 2015; Powell and Roberts, 2017). In addition, CMC may affect the quality and outcomes of collaboration, which highly depend on interaction quality (Curşeu et al., 2015; Meslec et al., 2016). Finally, because interactions differ from face-to-face, different social skills may become beneficial in CMC environments.

Emotions are accompanied by physiological states. In psychophysiology, psychological states are evaluated according to physiological responses, such as heart rate or facial muscle activity. Due to empathic abilities, physiological states tend to assimilate interpersonally during interactions, which may cause physiological synchrony (Cacioppo et al., 2001). The study of physiological synchrony aims to provide information, for example, about empathic processes by detecting concurrent changes in physiological signals of interacting individuals (Järvelä et al., 2021). Electrodermal activity (EDA) is a physiological measure of sympathetic arousal indexed by the conductivity of the skin. EDA has been connected to empathic experiences and outcomes of collaboration in several studies (Kazi et al., 2021; Marci and Orr, 2006; Messina et al., 2013). However, according to previous findings, EDA synchrony is sensitive to context and may not emerge when socioemotional information is restricted, as in CMC (Järvelä et al., 2021; Salminen et al., 2019).

This thesis aims to uncover underlying aspects of successful collaboration in CMC environments. Connections between dyadic collaboration, empathic skills, and EDA synchrony are studied with statistical methods. We evaluate whether different empathic skills impact collaborative success, whether empathy affects emergence of physiological synchrony, and whether EDA synchrony is associated with collaborative success in a virtual environment. In addition, We ask whether EDA synchrony emerges during interaction in VR during a collaborative task.

In the following chapters, I will first review prior literature on empathy, collaboration, and physiology of interaction. This review also covers interconnections between these social phenomena, and recent understanding of how CMC impacts on empathy, collaboration, and physiological synchrony, and lastly our research questions are framed. In Chapter 2, I will present our experimental design and tools to study the questions of interest. In Chapter 3, I will present our results and finally, in Chapter 4, provide a discussion of how these findings are reflected by the current understanding.

1.1 Empathy

Empathy is a complex, multidimensional phenomenon. In a broad sense empathy can be defined as an individual's affective response to a perceived or imagined emotional state (Cuff et al., 2016). Empathy is a deeply embedded and innate capacity of human nature which plays a critical role in social behaviors (Prochazkova and Kret, 2017). Empathic abilities are necessary for successful interaction and forming and maintaining meaningful interpersonal relationships (Leiberg and Anders, 2006). Babies show emotional responsiveness already in their first days of life, and children display empathic concern before they can verbally express such understanding (Meltzoff and Decety, 2003; Zahn-Waxler et al., 1992). Regard for others is essential for psychosocial development and mental health, whereas deficits in empathy markedly characterize social and emotional problems (Zahn-Waxler and Radke-Yarrow, 1990).

Human empathy has long evolutionary roots, answering to demands of group living and supported by parental attachment relationships (Decety and Svetlova, 2012; Waal, 2008). It is suggested that the complex social environment of primates has generated a unique evolutionary driving force which has pushed relative brain size to increase enormously (Dunbar and Shultz, 2007). According to this hypothesis, social cognition is the cause rather than a consequence of human intelligence. However, empathy does not only characterize human social life, but empathic behavior is a common trait in other group-living animals as well (Waal and Preston, 2017).

Besides a longstanding research tradition, the concept of empathy lacks a precise definition, and many authors accommodate related processes into the concept of empathy, such as sympathy and empathic behavior (Cuff et al., 2016). Empathy evokes a subject to feel as another, which is basically the same emotion between the subject and the target. In contrast, sympathy refers to feeling for another and provokes different emotion, such as pity or compassion. Empathic behavior, also termed as altruistic or prosocial behavior, refers to an action to relieve distress of the target, such as consolation (Cuff et al., 2016). Despite their typical coexistence, they are regarded as distinct phenomena. Empathic response may be accompanied with sympathy and sympathy may give rise to helping behavior, yet not necessarily so (FeldmanHall et al., 2015; Preston and Hofelich, 2012). Unfortunately, the lack of conceptual consensus has led to the misuse of the term, which in turn has consequently yielded mixed results and biased clinical findings (Cuff et al., 2016).

Despite the conceptual confusion, the most prominent and accepted view is that human empathy includes two distinct yet interconnected components: cognitive empathy and affective empathy. Additionally, it is broadly accepted that human empathy has three primary constituents: affective response to another person, cognitive capacity to understand other's perspective, and regulatory mechanisms to differentiate self and other originated feelings (Decety and Jackson, 2004). In this thesis, the term empathy is defined to consist of two interactive components, affective empathy and cognitive empathy, which are examined in detail below.

1.1.1 Affective Empathy

Affective empathy refers to interpersonal, automatic processes which provide affective state matching between individuals during interaction. In order to resonate, people tend to pick up emotional cues unintentionally and unconsciously in social situations (Chartrand and van Baaren, 2009). Facial expressions, bodily gestures, tone of the voice, speech tempo and gaze direction are all socioemotional information which indicates a person's affective state. Expressing as well as reading these cues is natural and spontaneous during social interaction.

Interestingly, people do not merely understand the message behind socioemotional cues but tend to behaviorally mimic them in social situations (Chartrand and van Baaren, 2009). For example, a person might unconsciously copy their friend's body position, speech tempo and tone of voice while having a conversation. (e.g., Chartrand and Bargh (1999)). Simultaneously their bodily states converge, and the person engages in an emotional state similar to that of their friend (Prochazkova and Kret, 2017). This unconscious and automatic mimicry has a fundamental role in human social life: it allows adaptation to the emotional state of the other, and thus increases social bonding, fosters empathy and liking, and improves smooth interaction (Chartrand and Bargh, 1999; Decety and Jackson, 2004; Lakin and Chartrand, 2003).

According to neuroscientific findings experiencing and observing emotions as well as retrieving emotional memories all share highly overlapping neural resources (Niedenthal, 2007; Hein and Singer, 2008; Wood et al., 2016). The underlying component which connects internal and external states is called the perception-action mechanism (de Waal and Ferrari, 2010). Through the perception-action link, perceiving another's facial expression automatically activates observer's behavioral and autonomic systems associated with the same emotion, and thus, enables affective sharing (Kret, 2015).

Accordingly, a tendency to unconsciously mimic others is associated with a tendency to empathize (Chartrand and Bargh, 1999). The mirror neuron system provides a neural link between observed and performed activity (Rizzolatti and Craighero, 2004). As mirror neurons fire, they transform observed activity into similar motor responses in observer's nervous system (Rizzolatti and Craighero, 2004). Mirror neuron system is not specific to empathy alone, yet it has been argued to be a core mechanism of the affective empathic response (Iacoboni, 2009).

Extensive scientific evidence shows that affective coupling is a commonplace ability in group living animals and has a clear evolutionary adaptive advantage in, for example, predator avoidance (Waal and Preston, 2017; Decety and Svetlova, 2012). Simple affective coupling and human affective empathy are mostly different due to the intensity of shared emotions, and due to attentional targeting, i.e., whether one is self-focused or concentrated on the state of the other (Preston and Hofelich, 2012). In addition, affective empathy includes conscious self-other awareness (de Vignemont and Singer, 2006). In addition, without functioning regulatory capacity, affective empathy may lead to personal distress, e.g., feelings of anxiety, and aversive behavior (Eisenberg and Eggum, 2013).

1.1.2 Cognitive Empathy

Cognitive empathy refers to understanding another's emotional state at a conscious level. Cognitive empathy plays a role in explaining socioemotional cues and providing situational, context-related understanding in each situation. Whereas bottom-up, sensory- based mechanisms characterize affective empathy, cognitive empathy relies mainly on cognition- based, top-down mechanisms. In contrast with affective empathy, cognitive empathy is not dependent on external socioemotional cues. For example, people can empathize with an imaginary character without any external stimuli. High-level cognitive processes can, in turn, activate downstream bodily representations, and hence, elicit embodied affective states (Eisenberg and Eggum, 2013).

Understanding of others' emotional states requires an ability to make conscious distinctions between self- and other-originated emotions (Gallup and Platek, 2002). Empathy is not an all-or-nothing function, and despite its cognitive demands, empathic perspective-taking is not only a human ability (Waal and Preston, 2017). Some animal species are clearly able to differentiate others' intentions and needs from their own, thus, have some level of self-other awareness, and many perform prosocial behaviors, such as targeted helping (Waal and Preston, 2017). Some social species with high levels of encephalization (e.g., apes, elephants, and dolphins) express clear understanding of others' personal, specific needs and can flexibly behave accordingly (Waal and Preston, 2017).

Even though other species express relatively complex forms of empathy, according to current understanding, human empathy is uniquely flexible and advanced (Decety and Jackson, 2004; Decety and Svetlova, 2012). This is argued to be explained by the high-level cognitive capabilities: advanced perspective-taking ability, executive functions (e.g., attentional and inhibitory control, cognitive flexibility, working memory), and symbolic language.

Cognitive empathy and theory of mind (TOM) are closely related concepts. TOM is an ability to infer motivations, beliefs, intentions, and emotional states of others, which partly shares the same cognitive and neural resources as cognitive empathy (Frith and Frith, 1999; Schnell et al., 2011). Similarly with the most complex forms of cognitive empathy, TOM is almost without exception restricted to human cognition (Gallagher and Frith, 2003; Decety and Svetlova, 2012; Schnell et al., 2011). TOM skills, affective coupling and regulatory mechanisms function as a dynamic whole, which enables people to shift attention from personal distress towards concern for others, adopt another's subjective perspective with emotional distance, and regulate their own behavior accordingly in social situations Schnell et al. (2011); Decety and Svetlova (2012).

1.1.3 Models of Empathy

Social factors, such as liking, social closeness or group membership modulate empathic responding (Oveis et al., 2010; Stel et al., 2010; Stürmer et al., 2006). Motivation enhances socioemotional mimicry and people tend to unconsciously mimic those they wish to affiliate with (Carr and Winkielman, 2014; Lakin and Chartrand, 2003). Interestingly, situational and motivational factors impact even the most primitive forms of interpersonal affective coupling (Carr and Winkielman, 2014). Although affective sharing mechanisms are considered primitive and automatic, situational adaptation happens automatically, seamlessly, and often unconsciously (Carr and Winkielman, 2014).

Shamay-Tsoory et al. (2019) propose a model for selective affective alignment, which is a results from a primitive but nuanced learning process. According to their approach, people continuously monitor their social position in relation to others, and unconsciously aim at minimizing a social gap between self and others. During interaction, the brain creates top-down predictions of affective alignments. If the top-down prediction matches with bottom-up sensory feedback, the reward-system activates. In case of a detected misalignment, the perception-action link activates, consequently activating behavioral and affective coupling mechanisms. Social behavioral, emotional, and cognitive components function within the same system, constantly providing reciprocal information. Therefore, the impact of social factors may reach all levels of affective coupling comprehensively. Shamay-Tsoory et al. (2019).

Cognitive empathic response is generated by experience-based information processing mechanisms and people vary in empathic understanding. According to Preston and Hofelich (2012), empathic understanding results from top-down activation of one's own emotional and contextual representational network, which relates to subject's particular situation. In this way, activation of associative network yields neural state matching between subject and object, which is necessary, yet not sufficient for state matching. Empathic understanding may not occur if a subject lacks similar experience, or the memory is too distant to simulate re-experiencing. Moreover, although bottom-up affective sharing emerges, personal and situational attributes, such as lack of motivation or saliency of socioemotional cues, may prevent an empathic response. Thus, according to the model, empathic understanding requires a subject's attention and experience of a similar event. Preston and Hofelich (2012).

1.1.4 Empathy Measurements

Ability to experience empathy varies across individuals. Empathy is typically measured either on a trait or a state level. Trait empathy refers to an individual's innate empathic skills, which are thought to remain stable over time, whereas state empathy is a momentary experienced empathy met in a particular situation (Leiberg and Anders, 2006). Most experiments studying trait empathy rely on validated psychometric self-assessment questionnaires. Questionnaires often cover different subcomponents of empathy, such as affective and cognitive empathy, or empathic accuracy, which refers to correct judgement of another's emotional state. State level empathic experience can be assessed by using post-experiment self-assessment methods.

Most self-assessment questionnaires are multidimensional, and thus, divide empathic abilities into subscales to capture the complex nature of human empathy. In this study we use Interpersonal Reactivity Index (IRI), which is the most prominent and widely used trait empathy measurement (Davis, 1983; Chrysikou and Thompson, 2015). IRI consists of four subscales which reflect distinct but interconnected aspects of empathy. During the last decades due to lack of precise definitions of empathy and its subcomponents, IRI has been uniformly used as a two-factor model. Four factors are recombined into two, simply to represent cognitive and emotional empathy. However, as popular as the two-factor model of IRI has become, it does not rely on validated metrics, and therefore has yielded controversial results (Chrysikou and Thompson, 2015). Consequently, in this study we emphasize the initial four-factor model of IRI.

1.2 Computer-Mediated Communication (CMC)

CMC refers to human interaction which takes place on digital software platforms, including text-, audio- and video-based mediums, and virtual reality (VR). As opposed to composing a uniform construct, CMC environments vary widely in temporal and spatial dimension, modality, degree of user control and context. Therefore, support for interaction quality is different in each medium. Defining separate interactive aspects can help to understand, assess, and augment filtering effects.

First, each type of CMC media can be represented in scale of medium richness, which refers to the interface's general capacity to transmit verbal, vocal, and behavioral information. For example, text-based platforms represent the low end of the scale, whereas augmented VR is rated high. Second, different mediums vary in immediacy of feedback; they can allow either synchronous or asynchronous communication, which affects the development of reciprocal socioemotional processes (Praszkier, 2014). The third component is the quality of transmission, such as poor online connections, which can disturb synchrony and the flow of communication. Fourth, the communication content may provide specific attributions, such as symbols, emojis, avatars or webcam angles. These applications allow users to alter and enrich self-expression and create medium-specific cultural aspects during interactions.

1.2.1 Empathy in CMC

Previous studies show that people can experience empathy in CMC environments (Carrier et al., 2015; Powell and Roberts, 2017). Although CMC mediums often lack perceptible socioemotional cues, people create intimate, meaningful relationships online and solely text-based mediums are shown to be viable to evoke affective coupling (Kramer et al., 2014; Ferrara and Yang, 2015). However, the appearance of empathy in CMC differs from face-to-face interactions in both quality and quantity. CMC environments are reported to reduce empathy levels significantly compared to face-to-face interactions (Carrier et al., 2015). Forms of cognitive empathy appear prevalent in CMC environments, whereas empathic behavior remains rather scarce (Powell and Roberts, 2017). Findings indicate that despite the fact that empathic experiences can arise in CMC environments, empathy may emerge through atypical routes, such as overweighting the role of top-down networks, which can prospectively influence formation of interpersonal relationships and group level processes (Kim, 2000). In the following, two opposing theoretical approaches into the emergence of empathy in CMC environments are presented (Kim, 2000; Powell and Roberts, 2017).

First, "cues filtered out theories" state that compared to face-to-face interactions, CMC mediums always restrict exchange of nonverbal socioemotional cues at some level, thus, resulting in impersonality and disrupted empathy. For example, facial expressions, bodily gestures, and prosody, are partly or completely filtered out from text- or voice-based communication. Direct eye contact provides attentional and emotional information to a perceiver, however, the possibility is prevented even in most video-based communication platforms, therefore reducing affective arousal during interaction (Syrjämäki et al., 2020). Affective empathy is especially dependent on the direct exchange of sensory socioemotional cues, and temporal asynchrony in CMC may disturb dynamical affective coupling processes during interactions (Nummenmaa et al., 2008). Consequently, emergence of empathic processes in CMC environments may have particular emphasis on individual's abilities in cognitive empathy, personal experiences, and motivation (D'Urso and Rains, 2008).

Second, "social information processing" theory proposes that people adapt to new communication channels in order to affiliate and create social bonds (Walther, 1992). Even though forms of interaction differ significantly from natural embodied signals, people create meanings, develop personalized impressions and form intimate relationships via CMC (Walther, 1992). Interestingly, several studies indicate that textual emotional contents are directly processed in emotion-related ancient subcortical brain areas (Ziegler et al., 2018). Moreover, reading emotion -related words can elicit implicit, embodied affective responses, such as facial muscle activity (Ziegler et al., 2018). This direct link between affective sensory and high-level cognitive processing enables emotional contagion through artificial channels such as CMC (Kramer et al., 2014; Ferrara and Yang, 2015).

Interestingly, social information processing approach endorses that depending on contextual factors, CMC environments may have not only proportional, but increased potential for interpersonal bonding and empathic experiences (Tidwell and Walther, 2002). Due to the lack of sensory exchange and temporal demands, CMC mediums are proposed to release the individual from the distress of immediate social feedback, and therefore, enable more thoughtful and accurate self-expression (Bargh et al., 2002). In addition, due to anonymity some CMC environments are free from expectations and norms of real-life interactions, and enable selective self-disclosure (Jiang et al., 2013). Finally, anonymity contributes to group formation, increases the sense of closeness and belonging, as hidden individual differences tend to strengthen the salience of both interpersonal and ingroup similarities (Michinov et al., 2004; Bargh et al., 2002).

However, despite its plausible prospects, ubiquitous use of CMC has generated unfortunate consequences. Concurrently, as CMC entails potential to foster group formation, online groups have increased tendency for ingroup favoritism, such as depersonalization and stereotyping of outgroup members, and outgroup discrimination (Michinov et al., 2004). Hence, due to CMC's expanding influence on everyday life, there is a growing pressure to understand precursory processes triggering spontaneous empathic responses. Preston and Hofelich (2012) theoretical framework proposes that top-down empathic understanding requires personal experience of similar events, and indicates that situational factors, such as reduced saliency of socioemotional cues and lack of personal motivation, can prevent empathic response. Findings indicate that online empathy relies on individuals' cognitive processes to a large extent, and little is known how downstream routes in emergence of empathy could be augmented (Bargh et al., 2002; Powell and Roberts, 2017). Thus, it is not understood how absence or saliency of any specific information type affects emotional convergence. In order to foster empathy in CMC environments, socioemotional processes need to be understood in more detail.

1.2.2 VR Environments

From the perspective of CMC, VR technologies bring novel tools to study social interactions. Technological solutions determine the quality of interactions, and thus have the potential to improve or distract social processes. Immersive technologies, such as VR environments are stretching the boundaries of interaction beyond typical forms, providing versatile possibilities to selectively include, exclude and modify interactive aspects.

According to recent studies, socioemotional processes in CMC can be augmented by providing socially relevant feedback during interactions (Järvelä et al., 2021; Salminen et al., 2019). Biofeedback of interactive partner's concurrent physiological state (e.g., visualized heartbeats) during CMC impacts emotions, social presence, and inter-personal attraction (Chanel et al., 2010). For example, deploying biofeedback in VR is shown to increase experienced empathy and physiological coupling between participants (Järvelä et al., 2021; Salminen et al., 2019). In addition, VR can be used to motivate empathy towards unfamiliar groups, such as animals, through immersive simulations where one can experience reality from other's position (Hannans et al., 2021; Shin, 2018; Ventura et al., 2021).

In this study, we use VR to provide rich, engaging task environment and to control the exchange of visual affective cues during the experiment.

1.3 Collaborative Task Performance

An ability to work effectively in dynamic groups has always been a fundamental part of human behavior. Prehistoric human populations survived because they could hunt, raise children, and protect their communities in collaborative groups (McLoone and Smead, 2014; Tomasello et al., 2012). In modern life, cooperation skills are still relevant; successful achievement of shared goals touches everyday life from work life to political activities, mass transit, and team sports.

Underlying determinants of group performance have been an interest of both scholars and practitioners for over 70 years (Kozlowski and Ilgen, 2006). According to current understanding, collaborative actions rely on emergent group processes, and include cognitive, affective/motivational, and behavioral aspects (Kozlowski and Ilgen, 2006). Although groups consist of individuals and their skills, collaborative performance is influenced by group level aspects rather than being a direct sum of individual skills and investments. For instance, a wide range of studies has connected collaborative task performance with group cohesion and group level satisfaction (Venkatesh and Windeler, 2012).

Work groups can be understood as emergent information processing units, where individuals share and combine their cognitive competences into a group level performance during interpersonal interactions. Quality of these interactions is crucial to perform effectively as a group. Indeed, according to a recent study, social skills of group members are important for collaborative success (Meslec et al., 2016). Some studies claim that instead of being significantly affected by team members' IQ, success in group- level performance is better explained by group members' social sensitivity, diverse group composition, and turn-taking equality (Chikersal et al., 2017; Engel et al., 2014; Woolley et al., 2010, 2015). In addition, Meslec et al. (2016) suggest that emergent group performance is a fragile process, and an individual, socially maladaptive group member can disrupt group coordination, thus negatively affecting the performance.

1.3.1 Empathy and Collaborative Task Performance

Collaborative actions require similar skills to those that enable people to behave empathically. Successful cooperation requires coordinated action, and therefore, an ability to interpret others' intentions, behavioral adaptation and self-regulation. Literature indicates that both bottom-up and top-down mechanisms have a prevalent role in cooperative success Tomprou et al. (2021).

Affective empathy enables efficient and smooth interaction, because behavioral and affective coupling provide a fast and spontaneous way to adapt to other's mental state

(Wood et al., 2016). Recent studies indicate that rather than forming slowly with trust and attachment, underlying dynamics of group performance emerge quickly (Tomprou et al., 2021; Woolley et al., 2010). Affective coupling is found to emerge spontaneously during cooperative task performance and cooperative success is related to the richness of interactions (Behrens et al., 2020; Mønster et al., 2015).

Behavioral mimicry has been consistently shown to promote cooperative action (Behrens et al., 2020; Chikersal et al., 2017; Gordon et al., 2020; Wiltermuth and Heath, 2009). Synchronic behavior and smiling predict group cohesion (Gordon et al., 2020; Mønster et al., 2015) and perceived affective sharing enhances individual's group alignment (Knight and Eisenkraft, 2015). Group- level affective states are important mediators of group functioning (Knight and Eisenkraft, 2015; Páez et al., 2015). Behaviorally shared positive feelings promote social integration, cooperation, formation of social identity and collective self-esteem, improve group cohesion and collaborative task performance, and decrease conflict (Barsade, 2002; Gordon et al., 2020; Knight and Eisenkraft, 2015; Páez et al., 2015). To conclude, important underlying aspects of group processes emerge partly through fast, subconscious neural routes.

Considering top-down mechanisms, TOM, a widely acknowledged component of cognitive empathy, is connected to group-level task performance in several studies (Engel et al., 2014; Woolley et al., 2010). An ability to correctly recognize and respond to each other's emotional states is understood to help group members to coordinate and regulate their behavior during performance (Meslec et al., 2016). It is suggested that groups with socially- talented members tend to develop group synergy, which may ease group coordination and task adjustment (Curşeu et al., 2015; Meslec et al., 2016). In addition, group-level TOM skills are connected to group cohesiveness and effectiveness, and decreased conflict (Curşeu et al., 2015).

1.3.2 CMC and Collaborative Task Performance

At present, collaborative teams often work in online environments. Despite the convincing line of research in group performance, understanding how technology impacts quality and outcomes of collaboration remains poor (Venkatesh and Windeler, 2012). As already discussed, interaction quality is crucial for successful, emergent group performance, and interaction is different via CMC versus face-to-face. Group members' social abilities are important for smooth interactions, and TOM skills are found to equally benefit group performance in online environments as in face-to-face collaboration (Engel et al., 2014).

Technology has the potential to support performance, however, it is not clear how performance could be modulated. Some findings suggest that successful collaboration is related to the increased richness of interaction (Behrens et al., 2020)). By facilitating the richness of interactions, team cohesion, and thus, team performance can be improved (Venkatesh and Windeler, 2012). However, studies have yielded controversial results related to richness. Tomprou et al. (2021) showed that lack of visual cues enabled team members to synchronize their vocal cues and speaking turns more effectively, and improved team performance. If emergent group processes were understood in more detail, systems could be designed to support interaction and formation of group dynamics, for example, optimizing task relevant information, or regulating influence of a dominating or maladaptive team member.

1.4 Psychophysiology of Interaction

Psychophysiology uses one or more physiological measurements to assess psychological states (Cacioppo et al., 2001). Physiological processes are an important prerequisite to emotions, cognition and behavior, and therefore changing bodily signals can be measured and connected to psychological events (Levenson, 2014). Psychophysiological methods enable continuous data collection, and most provide high temporal resolution. Physiological data detects activity that occurs before conscious appraisal, such as minute deviations in autonomic nervous system, and compared to traditional self-report measurements, lacks introspective bias. Without need for verbal report, psychophysiological methods can be used to study, for example, babies or non-human species (Feldman et al., 2011).

Physiological synchrony aims to identify systematic co-dependency of physiological activity between two or more individuals. This approach has brought novel tools to understand social phenomena, especially unconscious aspects of interaction. In addition, technological development has enabled recording outside the lab, providing eligible ecological validity. In the following chapter, the main focus is on electrodermal activity (EDA) synchrony, however, interesesting insightgs to other forms of physiological synchrony are also presented.

1.4.1 Autonomic Nervous System

Autonomic nervous system (ANS) consists of two main branches: sympathetic nervous system (SNS) and parasympathetic nervous system (PNS). Whereas PNS is more activated during the resting state, SNS responds to quick changes in external and internal environments, yet both branches function simultaneously. The main purposes of ANS are to maintain homeostatic balance in the body, and concurrently supply adaptive short-term deviations respective to environmental challenges and opportunities (Levenson, 2014).

In addition, the ANS coordinates connections between emotions and cognitive processes, hence, generation, expression, experiencing and recognizing emotions are all densely tied into ANS activity (Levenson, 2014). During the last decades research has tried to specify autonomic signatures of discrete emotions (Kreibig, 2010; Levenson, 2014; Mauss and Robinson, 2009). At present, the existence of emotion specific ANS patterns remain unclear, however emotion related arousal (intensity) and valence (approach/avoid) are associated with different ANS measures (Kreibig, 2010; Mauss and Robinson, 2009).

Psychophysiology offers a variety of techniques to measure complex interaction of SNS and PNS activity, such as heart rate, respiratory rate, electrodermal activity, and electrical activity of the brain. Each of these signals have their own characteristics with respect to ANS overall activity (Kreibig, 2010; Levenson, 2014; Palumbo et al., 2017). For example, electrodermal measures reflect SNS activation alone, whereas cardiac measures, such as interbeat interval (IBI) and heart rate variability (HRV) detect activation of both SNS and PNS branches.

Electrodermal Activity (EDA) EDA is a common psychophysiological measure of SNS activation. It is an indirect measure of eccrine sweat gland activation, which are innervated purely by the SNS, hence, EDA is not influenced by PNS activity (Cacioppo et al., 2001). SNS activation coordinates deviations from resting state, and changes in EDA signal reflect emotional arousal and reactivity (Kreibig, 2010). Consequently, increase is associated with emotions related to action preparation, which accompanies cognitive or emotional load. These emotions include fear, anger, disgust, embarrassment, amusement, pride, surprise, and suspense (Kreibig, 2010). Decrease in EDA occurs concurrently with passive motivational state, which characterizes emotions of sadness, contentment, and relief (Kreibig, 2010).

Skin Conductance (SC) signal is a physiological measurement which detects changes in EDA. SC is recorded between two sensors attached directly on the skin surface, commonly placed on palms or fingers. SC increases when eccrine sweat pores open and moisturize the skin, and decreases as sweat evaporates. SC signal consists of two subcomponents which can be extracted from raw data and analyzed independently: tonic skin conductance level (SCL) and phasic skin conductance response (SCR). These subcomponents vary in their signal shape and emotional dimension they reflect: SCL signal reflects long- term, slow variation in SNS activity and increases during arousal, whereas SCR signal detects fast, spike-like changes, and reflects emotional valence (Cacioppo et al., 2001). Typical values of SCL vary between 2 and 20 µS and the signal changes between 1 and 3 µS. The common size of SCR is between .1 and 1.0 µS. SCR signal provides high temporal responsiveness and a typial latency between stimulus onset and SCR initiation is 1-3 S, and 1-3 S from the initiation to its peak. Half-recovery time is between 2 and 10 S.

(Cacioppo et al., 2001). According to the current literature, emotion-specific increases in SCR and SCL are interdependent, changes in signals are either co-directional, or neutral across the experiments (Kreibig, 2010).

1.4.2 Interpersonal Autonomic Synchrony

ANS synchrony of peoples' autonomic states is shown to be a common social phenomenon which has been studied in various populations, including parent-child relations, psychotherapy, teammates, and romantic couples (Golland et al., 2015; Levenson, 2014; Palumbo et al., 2017). Findings indicate that ANS synchrony emerges independently, regardless of behavioral and situational factors, sensory modality, valence, or relationship type, and even mere co-presence causes ANS state matching (Golland et al., 2015; Palumbo et al., 2017). However, other studies show that ANS synchrony is highly context dependent, and as contrary to emerging automatically between any individuals, synchrony is a complex, relational phenomenon which can be regulated by cognitive processes (Danyluck and Page-Gould, 2019).

Theoretical controversies are partly due to the large methodological variety in the field. Even though the study of interpersonal physiological dynamics is growing, the field still lacks scientific standards, and therefore comparison of different studies and theory building remain complex (Kazi et al., 2021; Palumbo et al., 2017; Schneider et al., 2020). Data analysis methods, terminology and experimental setups vary from study to study, and patterns of synchrony have not been carefully studied. Recently, Schneider et al. (2020) tested four existing methods to calculate EDA synchrony during a dyadic collaborative learning task and found that different methods were associated with learning outcomes differently.

1.4.3 Psychophysiology of Empathy

A number of social phenomena are connected to ANS synchrony, including empathy (Palumbo et al., 2017). People involved in social interactions will constantly observe ANS-originated emotional signals, such as pupil diameter, blushing, heart rate and breathing rhythm, which are transformed into similar activity in observer's ANS (Kret, 2015). Perception-action coupling mechanisms recruit both motor and autonomic synchrony, and thus enable affective coupling across the nervous system (Hatfield et al., 1993; Kret, 2015; Rizzolatti and Craighero, 2004).

Some researchers have suggested affective empathy to be an underlying explanation for interpersonal ANS convergence (Palumbo et al., 2017)). However, ANS synchrony occurs independently from empathy, and some aspects of empathy may predict synchrony more than others (Palumbo et al., 2017). Different components of empathy partly rely on separate neurological mechanisms and therefore may be expressed differently in ANS. The role of mirroring activity is emphasized in affective empathy, and it may produce ANS coupling more than cognitive empathy (Nummenmaa et al., 2008). Cognitive empathy may support interpersonal, co-regulatory activities,; this, in some situations, may imply interpersonal asynchrony in ANS activation (Coutinho et al., 2019; Feldman, 2012).

According to existing findings, ANS signals reflect empathic responses independent of context. Oliveira-Silva and Gonçalves (2011) found associations between empathic responding and intrapersonal IBI, and Järvelä et al. (2014) associated interpersonal IBI synchrony with both trait tendency to empathize and state empathy during gaming activity. Yet neither of the studies found connections between EDA and empathy (Järvelä et al., 2014; Oliveira-Silva and Gonçalves, 2011). Salminen et al. (2019) connected cortical activity synchrony (EEG frontal asymmetry) to perceived empathy during interactive VR environment meditation task. In their study, biofeedback enhanced the subjective empathic experience and cortical synchrony between participants (Salminen et al., 2019). In line with other findings, EDA synchrony measured during this experiment was non-significant, and not associated with either empathic experience, or richness of communication (Järvelä et al., 2021).

However, contradictory to these findings, the study of therapist-client interaction has repeatedly connected empathic experience with increased EDA synchrony (Marci and Orr, 2006; Messina et al., 2013). In addition, moments of high EDA synchrony has occurred simultaneously with an increased number of socioemotional cues (Marci et al., 2007). Coutinho et al. (2019), studied romantic couples and found that empathic skills and interaction valence determined the occurrence of EDA synchrony. Synchrony was increased during negative interactions, and synchrony during positive interactions was modulated with male partners' trait empathy (Coutinho et al., 2019). Additionally, Levenson and Ruef (1992) found that EDA synchrony, but none of the PNS measures, was connected to empathic accuracy, which refers to accurate judgements of other's emotional state (Levenson and Ruef, 1992).

Although research of neurobiological mechanisms of empathy is abundant, connections between ANS synchrony and trait empathy remain rather underexplored, and studies have yielded mixed results. (Coutinho et al., 2019), for example, found no significant connection between IRI subscales and EDA synchrony. These findings suggest that EDA synchrony has context dependent connection to empathic experience, yet association can reflect more general phenomena, such as social presence (Chanel et al., 2012; Järvelä et al., 2014).

1.4.4 Psychophysiology of Collaborative Task Performance

During collaboration, group dynamics change over time, and synchrony analysis of group members' physiology may help to capture dynamical, emergent processes between team inputs and outcomes. Indeed, several studies have connected physiological synchrony with group performance (Kazi et al., 2021). Behavioral and ANS synchrony is associated with group cohesion and performance outcomes (Elkins et al., 2009; Gordon et al., 2020; Henning et al., 2001), collaborative problem solving (Elkins et al., 2009), collaborative learning, teamwork effectiveness (Henning et al., 2001), and group-level self-regulation ability (Malmberg et al., 2019). However, despite the repeatedly found connections to positive outcomes, ANS synchrony is shown to increase during conflicting interactions, and strengthen during competitive gaming compared to cooperative condition (Chanel et al., 2012). These results imply that synchrony patterns need more fine-grained definitions to provide clear theoretical implications.

Similarly, EDA synchrony is associated with both positive and negative aspects in collaboration, and it remains unsure what construct EDA synchrony reflects in collaboration, and whether different synchrony methods detect the same construct. EDA synchrony is related to co-operative success (Behrens et al., 2020), task completion time, improved group performance (Henning et al., 2001; Montague et al., 2014), and group satisfaction (Chikersal et al., 2017). Yet, it also relates to negative affect and group tension (Mønster et al., 2015). Dindar et al. (2020) failed to associate EDA synchrony with task performance, but synchrony periods indicated group-level collective mental effort. In addition, richness of interaction is suggested to impact outcomes of synchrony; Behrens et al. (2020) found that EDA synchrony predicts cooperation when participants could see each other, but in face-blocked condition the effect was dampened.

1.4.5 Physiological Synchrony During CMC

CMC environments engender special challenges in emergence of physiological synchrony because interactive partners are dislocated, and interaction often lacks direct socioemotional cues. Embodied synchrony is at least partly dependent on sensory information and studies consistently show that ANS synchrony increases due to richness of interactions (Chanel et al., 2012; Salminen et al., 2019). Additionally, ANS synchrony is significantly stronger among physically present interactive partners and can occur during mere physical co-presence without direct interaction (Golland et al., 2015; Palumbo et al., 2017). Hence, synchrony during CMC may emerge through atypical routes and the extent to which co-presence or interaction based on socioemotional cues is necessary, is yet largely unexplored.

As already discussed in Chapter 1.2., some forms of interpersonal synchrony, such as affective coupling, and vocal synchrony can take place in CMC environments (Kramer et al., 2014; Tomprou et al., 2021). Even though increased synchrony relates to the richness of information, synchrony is found during interactions with restricted sensory modalities. For example, Mønster et al. (2015) found EDA and facial "smiling" muscle activity synchrony in absence of vocal cues during a cooperative task. Behrens et al. (2020) found dyadic EDA synchrony in face-blocked condition during cooperative task, yet synchrony predicted cooperative success only during face-to-face contact. Järvelä et al. (2021)) found cortical activity synchrony, but no significant EDA synchrony, during a VR meditation task where only artificial visualizations of ANS activity were shown to subjects.

However, autonomic synchrony can occur independently from co-presence and across modalities (Palumbo et al., 2017). According to Shamay-Tsoory et al. (2019) (presented in Chapter 1.1.3.) affective, behavioral and cognitive processes align within the nervous system, and the activation spreads across affective and cognitive systems spontaneously. Following Shamay-Tsoory et al. (2019) framework, each form of information has potential to evoke an overall socio-emotional system, and VR environments provide interesting settings to determine the role of different modalities in the emergence of ANS synchrony.

EDA Synchrony and Task Performance During CMC Formation of team dynamics is a sensitive, context dependent process, and remains is unclear whether EDA synchrony predicts similar outcomes in CMC as in real life.

According to *cues filtered out framework*, reduced richness may harm social processes in CMC, such as social bonding, group performance and group dynamics. Behrens et al. (2020) found that EDA synchrony predicted cooperative task performance only in face-to-face conditions, and absence of visual cues dampened the effect. On the other hand, *social information processing* theory proposes that people spontaneously adapt into new communication channels in order to affiliate. Tomprou et al. (2021) found that reduction of nonverbal cues helped team members to synchronize vocal cues during video conferencing.

So far, there is only a little evidence that ANS synchrony predicts collaborative performance in CMC environments. However, due to abundant connections during face-to-face collaboration, it may be expected that EDA synchrony is connected to better task performance in VR environment.

1.5 Research Questions

Concluding from the literature presented, we have defined three research questions. In attempts to seek new insights to the gaps in the current understanding, this work is framed to study the connections between empathic skills and EDA synchrony, EDA synchrony and dyadic collaboration, and empathic skills and collaborative task performance in VR environment. In addition, we explore whether dyadic EDA synchrony occurs in a VR environment during a collaborative task.

Research Question 1: *a) Does trait empathy predict EDA synchrony in VR environment? b) Does trait empathy predict collaborative task performance in VR environment?*

Research Question 2: *Is EDA synchrony associated with collaborative task performance in VR environment?*

Research Question 3: *Does EDA synchrony occur during a joint problem-solving task in VR environment without the exchange of visual cues?*

2 Methods

2.1 The Study

2.1.1 Subjects

Sixty-six participants (33 pairs) were recruited via mailing lists of student unions of University of Helsinki and social media. All participants were right-handed and Finnish-speaking and had normal or corrected-to-normal vision.

Participants were recruited individually, paired randomly and met their collaborative partner for the first time in the VR environment. Experimental setup was symmetric within and between dyads: all participants had similar roles in task performance, and there were no separating grouping factors between dyads. Participants' and dyadic descriptive statistics are reported in the Results section.

The study protocol was approved by The University of Helsinki Ethical Review Board in the Humanities and Social and Behavioural Sciences, and all participants signed an informed consent form.

2.1.2 Psychometric Tests

Interpersonal Reactivity Index (IRI) IRI is a common psychometric tool in the study of human empathy Davis (1983). It's a 28-item self-report questionnaire which divides empathy into four 7-item subscales: perspective taking (PT), fantasy (FT), empathic concern (EC) and personal distress (PD). PT scale assesses individual's spontaneous tendency to reach other's psychological point of view; FS ability to imaginatively transpose oneself with fictitious character; EC other-oriented sympathy and concern; PD self-oriented distress in emotional interpersonal settings. PT and FS are regarded to reflect cognitive aspects of empathy, whereas EC and PD are aspects of affective empathy.

Reading the Mind in the Eyes (RME) RME is a simple and most widely used test of emotion recognition and is considered to reflect TOM skills (Baron-Cohen et al., 2001). RME consists of 36 still pictures of eye regions, some accompanied with emotional cues and others emotionally neutral. Respondents need to match the pictures with the correct semantic definition of the mental state. RME is a close-ended question survey and respondents are expected to use rapid, unconscious and automatic understanding during the task.

Wechsler Adult Intelligence Scale-III (WAIS-III) WAIS-III is a test pattern to assess cognitive abilities of adults (Wechsler, 1955). It contains 11 subtests, from which a block design subtest was used to assess individual performance in this study. The block design subtest represents a valid measurement of individual visuo-spatial task performance, which correlates highly with overall performance in the collaborative block design (Wikström et al., 2020). Scores of the block design subtest were used in the analyses to control the impact of individual skills in collaborative performance.

2.1.3 Collaborative Block Design

Recently, Wikström et al. (2020) developed a novel method to assess and quantify dyadic task performance. The Collaborative Block Design is a visuo-spatial joint problem-solving task, where participants need to cooperatively finish a series of 3D puzzles in a VR environment. The task roles are symmetric, and two-way cooperative information sharing is required to complete the task. When individual skills are controlled, Collaborative Block Design can be used to study interpersonal and environmental aspects of pair performance (Wikström et al., 2020).

The task procedure begins with both dyad participants having a two-dimensional view of a three-dimensional block configuration, each from a different angle. To figure out the 3D configuration of the blocks, dyad participants need to share information of their view either verbally or visually by placing the blocks during the task. The shapes include cube, cylinder, sphere, pyramid, cone, long cuboid and long cylinder, and each shape resembles at least one other shape in 2D side projection. There were seven different shapes in two colors, which makes 14 blocks in total. These blocks were organized into configurations in varying levels of difficulty. For more detailed information, see (Wikström et al., 2020).

2.1.4 The Procedure

First, participants filled the background questionnaire and the self-assessment empathy pretests. Then the block design subtask of the WAIS-III test battery was completed together with the researcher. After that the participants were instructed how to do the collaborative block design task and familiarized with both the 2D and 3D view of the blocks and the experimental VR environment. EDA recording devices were placed, and participants were supplied with a VR headset, headphones, microphone and handheld controllers. Before the actual task the baseline recordings were performed, where participants sat and walked in a neutral VR environment for 10 minutes. Participants were in separate rooms throughout the experiment.

The VR environment contained a space where participants had a set of all seven different 3D blocks and 2D view of the task solution (see Figure 1). Participants could freely grab, move and rotate blocks with handheld controllers. They could place the blocks on a virtual table for suggestions of the solution, which was viewed by their collaborative partner, and each participant could only see the 2D version of the other's suggestions. They communicated through a microphone and headphones during the task. After they agreed on a configuration solution, participants reported the task as completed. The environment returned automatically to its initial settings, and the next task could begin.

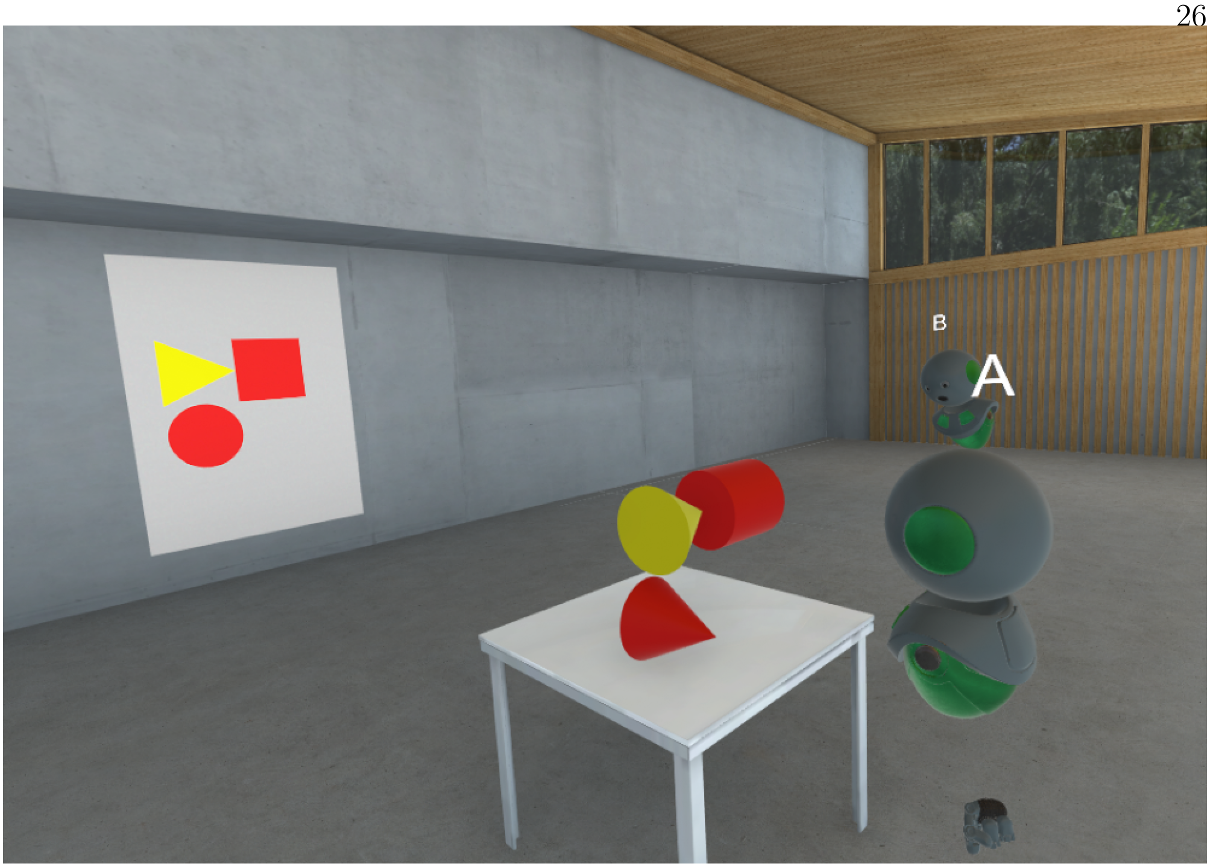


Figure 1: Screen capture from the VR task environment.

The tasks were performed in two sets of five puzzles, ranging from easy to more challenging within each set. The research assistant monitored the experiment and the data recordings during the experiment, and took notes on any interferences which could impact the following data analyses.

2.1.5 Performance Scoring

The task performance measurement followed the scoring system developed by Wikström et al. (2020), where dyadic performance scores are based on completion times but also takes into account the order of the tasks.

The two sets of puzzles were half-split balanced in the sample to control the learning effect. Trial time and success/failure to find correct solution of each task were recorded. Maximum time was set to 15 minutes and if exceeded, the task was marked as failed. Pairs were divided into tertiles according to their performance time on each task, where a pair gained 3 points if in the fastest tertile, 2 points in the second, and 1 point in the third tertile. Pairs with incorrect solution or performance time over 15 mins were assigned 0 points. The scores were summed for each pair to represent their overall performance across all tasks.

2.1.6 EDA Recordings

Participants' SC was measured during task performance in VR environment. The electrodes were placed on the middle and the ring fingers of the left hand of each participant. The recording equipment was Nexus 10 Mark II and the data was collected with BioTrace+ software.

2.1.7 Preprocessing

SC data was preprocessed with the Ledalab toolbox v3.4.9 in Matlab (r2019). First, artefacts were detected by visual inspection and interpolated with Ledalab curve fitting tool. Data sections which clearly differed from typical SC signal amplitude change and exceeded 0.05µS minimum amplitude criteria, were corrected. Following the literature, the data was low-pass filtered with 1st order Butterworth low-pass filter with cut-off criterion of 5 Hz. Signals were downsampled to 8 Hz according to closest value of Nyquist Rate: minimum SCR from initiation to the peak is 0.5 s (2 Hz) and recovery time 2 s (0.5 Hz) (Cacioppo et al., 2001), and therefore calculated Nyquist rate is $(2 + 0.5) * 2 = 5Hz < 8Hz$. Then, SC signals were extracted into SCL and SCR components using continuous decomposition analysis, which was based on-negative deconvolution method (Benedek 2010) Four optimization cycles were run, and finally the data was exported from Ledalab. The following signal analyses were run with Matlab r2019 software.

2.2 EDA Synchrony Indices

Schneider et al. (2020) recent findings propose that different synchrony methods are associated collaborative learning outcomes differently, and therefore, may partly reflect separate phenomena. For this reason we have decided to study two previously used methods to measure synchrony, and test whether they are codirectional.

2.2.1 SC Concordance Index

Concordance index is a correlational EDA synchrony method, which detects moment-to-moment directional agreement of participants signal changes. The procedure is originally introduced by Marci et al. (2007) and has been mainly used to study physiological synchrony during therapy sessions (Karvonen et al., 2016; Messina et al., 2013). SC concordance index was calculated for each dyad.

First, preprocessed SC signal was transformed into average slopes by calculating the difference of amplitude means of two overlapping 5 s windows in 1 s step $[(x(t) - x(t-1)]$. Second, Pearson correlation coefficients were calculated between participant's average slopes throughout the data in 15 s successive time-locked windows. Third, the dyadic concordance indices were created by dividing the sum of overall positive correlations by the sum of all negative correlations across the session. Finally a natural logarithm was applied to the resulting value.

In previous analyses, the original study used fixed lag-zero, whereas others have tested lags ranging from 0 to 4 and 7 s (Karvonen et al., 2016; Marci et al., 2007; Messina et al., 2013). However, due to symmetric experimental design we did not expect that consistent lag to occur and therefore chose to use fixed lag-zero as the original analysis using this method.

2.2.2 SCR Correlation Analysis

SCR correlation is correlational sliding window approach, which follows the method used in Järvelä et al. (2021) experiment. It is a modified frequency domain analysis, where SCR signal spike frequencies are exchanged with standard deviations of continuous SRC signal, which can likewise be understood as an increase of signal spiking.

First, standard deviations of continuous SCR signals were calculated in 40 s sliding windows and 20 s overlap for each participant. Then dyadic Pearson correlation coefficients were calculated between obtained standard deviation values throughout the data. Järvelä et al. (2021) used permutation analysis to test the significance of synchrony values. However, due to high variation in the task performance times in our data, permutation tests could not be applied, and significance was tested with the Monte Carlo procedure.

2.2.3 Statistical Testing

Monte Carlo approximation was used to control for autocorrelation and to evaluate the statistical significance of synchrony values. The same procedure was used by Karvonen et al. (2016). Monte Carlo procedure consists in generation of 100 pairwise shuffled values and using 95th value as significance criteria to real synchrony value. Monte Carlo values were calculated similarly as the real synchrony values in both analyses, with the difference that participant 1 data were in correct order but connected with randomly chosen time windows of participant 2 across the data. The shuffled values were then set in ascending order, and if the real synchrony value proceeded 95th value, it was considered to reach .05 significance. The statistical detail for this method is presented and further discussed in a book 'Statistical Identification of Synchronous Spiking‘ (Victor and Dilorenzo, 2013).

2.3 Statistical Analyses

To see whether the SC Concordance and SCR correlation indices reflect similar psychological construct, dyadic Pearson correlation was calculated between the two dyadic indices across all dyads. Regression analyses were used to study whether the synchrony indices were related to overall task performance and whether an average dyadic empathy predicted the emergence of synchrony.

The first regression analyses were performed with synchrony values as an independent variable, and performance as a dependent variable. In the second series of analyses four IRI subfactors and RME values were independent and synchrony values dependent variables. In the third series the empathy measurements were independent variables and task performance a dependent variable. To avoid autocorrelation variables were studied independently in all analyses. Average points of WAIS-III subtest were controlled as independent variables in analyses where empathic skills were predicting task performance.

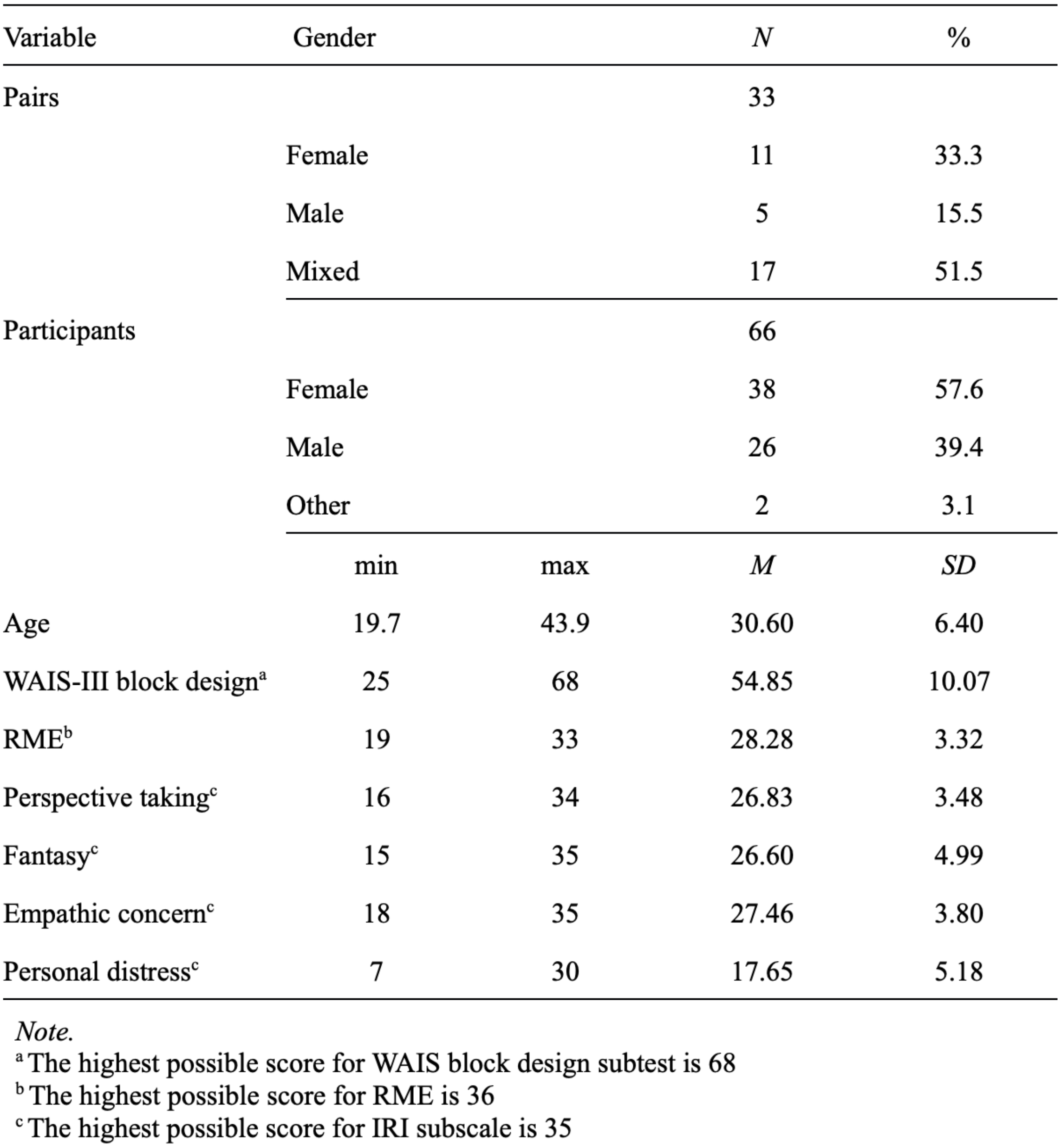
3 Results

3.1 Background Factors

Synchrony indices were successfully calculated for 29 dyads out of 33, and included in the final analyses (58 participants, 24 males, 33 females, 1 other). One of the pairs were excluded for knowing each other beforehand, and three pairs had insufficient data quality to proceed into the further analyses. Descriptive statistics of the sample and individual empathy scores can be seen in Table 1. Females scored higher in PD scale ($t(66)=2.47$, $p<.016$), and no other gender differences were found in RME and IRI subscales (P-values$>.097$).

Table 1

Participants' Pairwise and Individual Descriptive Statistics



Variable	Gender		*N*	%
Pairs			33	
	Female		11	33.3
	Male		5	15.5
	Mixed		17	51.5
Participants			66	
	Female		38	57.6
	Male		26	39.4
	Other		2	3.1
	min	max	*M*	*SD*
Age	19.7	43.9	30.60	6.40
WAIS-III block design[a]	25	68	54.85	10.07
RME[b]	19	33	28.28	3.32
Perspective taking[c]	16	34	26.83	3.48
Fantasy[c]	15	35	26.60	4.99
Empathic concern[c]	18	35	27.46	3.80
Personal distress[c]	7	30	17.65	5.18

Note.
[a] The highest possible score for WAIS block design subtest is 68
[b] The highest possible score for RME is 36
[c] The highest possible score for IRI subscale is 35

3.2 EDA Synchrony

Monte Carlo tests showed significance of 17.0% of the measured SC concordance indices and 31.0% of the SCR correlation indices. Overall ranges and statistical indicators of indices are presented in Table 2. Significant Pearson correlation between the indices was found ($r(27)=.42$, $p=.024$).

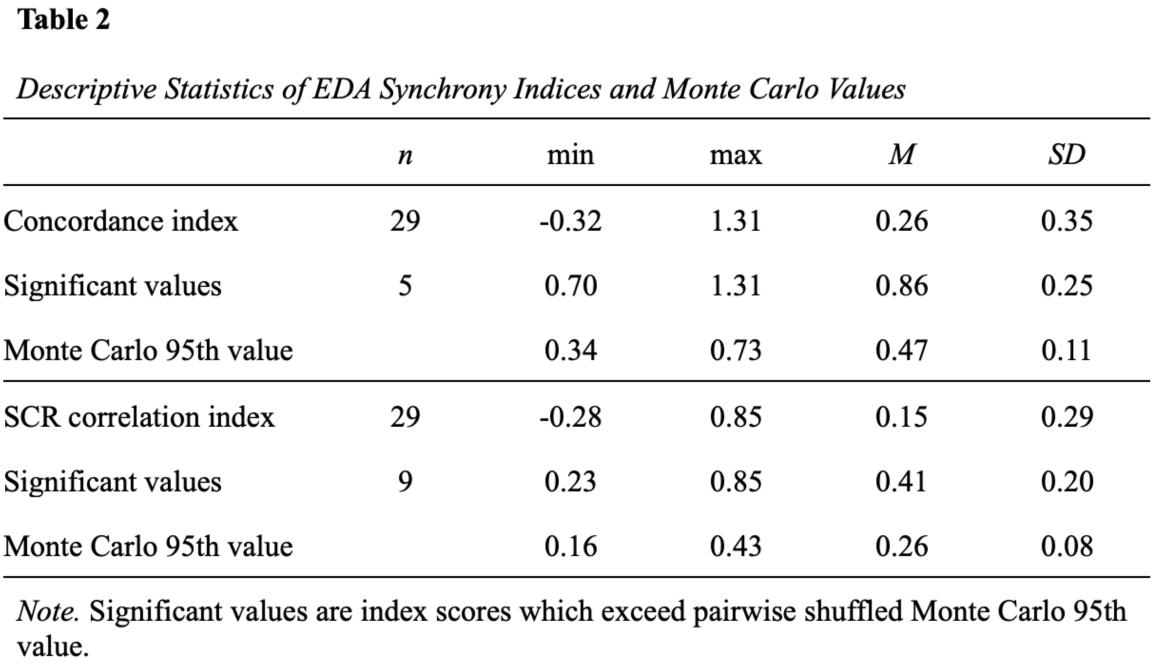


Table 2

Descriptive Statistics of EDA Synchrony Indices and Monte Carlo Values

	n	min	max	*M*	*SD*
Concordance index	29	-0.32	1.31	0.26	0.35
Significant values	5	0.70	1.31	0.86	0.25
Monte Carlo 95th value		0.34	0.73	0.47	0.11
SCR correlation index	29	-0.28	0.85	0.15	0.29
Significant values	9	0.23	0.85	0.41	0.20
Monte Carlo 95th value		0.16	0.43	0.26	0.08

Note. Significant values are index scores which exceed pairwise shuffled Monte Carlo 95th value.

3.3 Regression Analyses

No significant connections were found between EDA synchrony indices and IRI and RME, or EDA synchrony and task performance. RME scores and SCR correlation were weakly associated, however the connection did not reach statistical significance (t=1.76, $p<.09$). Associations between empathy and task performance can be found in Table 3. Positive connection was found between the PD scale and the performance points ($t(26)$=2.818, $p<.009$). In addition, connection with RME and performance was close to statistical significance ($t(26)$=1.895, $p<.068$).

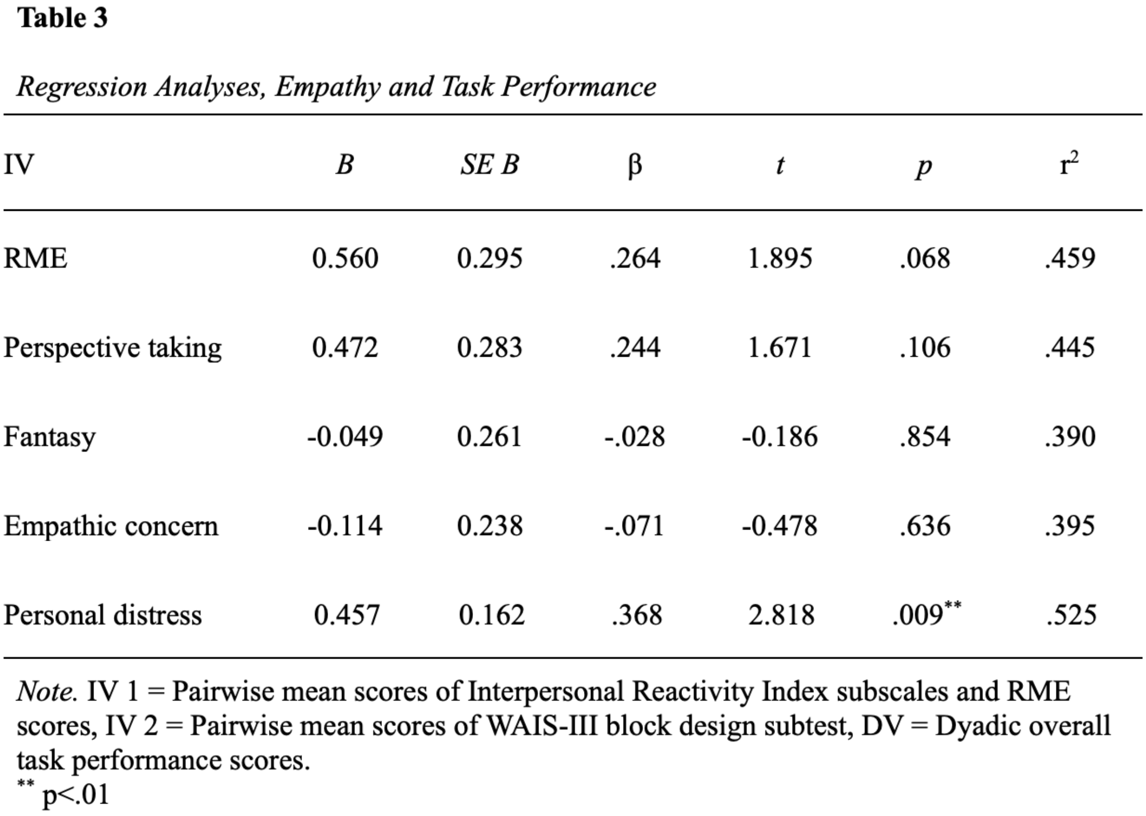


Table 3

Regression Analyses, Empathy and Task Performance

IV	*B*	*SE B*	β	*t*	*p*	r^2
RME	0.560	0.295	.264	1.895	.068	.459
Perspective taking	0.472	0.283	.244	1.671	.106	.445
Fantasy	-0.049	0.261	-.028	-0.186	.854	.390
Empathic concern	-0.114	0.238	-.071	-0.478	.636	.395
Personal distress	0.457	0.162	.368	2.818	.009**	.525

Note. IV 1 = Pairwise mean scores of Interpersonal Reactivity Index subscales and RME scores, IV 2 = Pairwise mean scores of WAIS-III block design subtest, DV = Dyadic overall task performance scores.
** p<.01

4 Discussion

The aim of this thesis was to investigate relations between empathic skills and collaboration in VR environment. Despite the increasing role of CMC in daily lives, the recent literature provides controversial picture of how reduced socioemotional richness impacts on interaction on social processes. In addition, we studied whether EDA synchrony emerged during collaborative performance, whether synchrony was influenced by empathic skills, and whether synchrony predicted pair performance in these settings.

Our first research question was to evaluate connections between trait empathy and EDA synchrony, and trait empathy and task performance in the VR environment. A positive trend was observed between RME and task performance. Although the connection was nonsignificant, it gains support from previous findings that TOM skills are beneficial in collaborative task performance equally online as in face-to-face collaboration (Engel et al., 2014). Interestingly, a significant positive connection was found between PD and task performance. According to previous understanding, the PD scale is related to tendency of social avoidance and maladaptive emotion regulation strategies, thus, it is not expected to enhance effective collaboration (Grynberg and López-Pérez, 2018; Curşeu et al., 2015).

However, CMC differs from face-to-face interaction and therefore may change the role of social abilities.

One interesting explanation for our findings is that CMC environments may offer 'a buffer' against affective coupling for individuals who tend to resonate with others with a low threshold. Affective coupling occurs spontaneously during interaction, and those who score high in the PD scale are regarded as more sensitive for subconscious, unvoluntary coupling, and lower in their emotion regulation capacities. *Social information processing* theory proposes that certain forms of CMC release individuals from distress of immediate social feedback, and therefore help to direct cognitive resources to relevant information. In CMC environments, as proposed by *cues filtered out* framework, subtle affective cues may not be salient enough to trigger coupling mechanisms of individuals with low emotional sensitivity, and consequently, empathic responses can be damped due to lack of stimulation, decreasing the quality of interaction (Grynberg and López-Pérez, 2018). However, emotionally sensitive people may benefit from their high tendency to resonate, and therefore experience empathy and social engagement during online interactions.

Although people adapt to communicate in CMC environments, empathic processes may rely increasingly on individual motivations and experiences. Group process theories indicate that due to reduced socioemotional information, ingroup similarities and between-group differences tend to become more salient, thus increasing risks of stereotyping, ingroup favoritism and misunderstanding on CMC platforms. However, recent work suggests that sensitivity to socioemotional signals may help to balance negative effects of reduced socioemotional richness in CMC. In a recent study, Bonfils et al. (2018) found that high scores in PD helped people to gain empathic understanding. Whereas well-functioning emotion regulation eases one's own distress, it tends to suppress overall emotional experience, and thus, an ability to understand others in distress (Bonfils et al., 2018). Their findings are in line with Preston and Hofelich (2012)'s framework of cognitive empathy, which states that to achieve true empathic understanding, an individual needs to have similar personal experiences.

This finding together with previous research reveal relations between the two opposing theories of how CMC impacts empathy. The framework presented here suggests that different social skills may become beneficial during CMC compared to face-to-face interaction and collaboration. While offering poor quality of socioemotional interaction, CMC environments may provide a buffer which allows emotionally-sensitive people to regulate their affective states and benefit from their rich internal experiences. To understand how CMC environments impact on collaboration and the role of empathy, there is a need for further study.

Second, we studied whether EDA synchrony is associated with collaborative problem-solving task performance in the VR environment. Even though EDA synchrony was present during the task, this study failed to find connections between synchrony and performance outcomes. This result is in line with Behrens et al. (2020) findings that EDA synchrony indicates task performance only when visual cues are available.

It remains unclear what is the influence of EDA synchrony in collaborative performance outcomes and recent literature provides mixed results. One possible explanation is that EDA synchrony supports task adjustment and motivation. Behavioral synchrony, which is associated with ANS synchrony, is connected to group alignment, positive group affect and group identity in real-life. In addition, Järvelä et al. (2021) connected EDA synchrony with social presence in VR environment, indicating that synchrony could support participants' personal task involvement. In this study, collaborative partners were newly introduced, and tasks were relatively short. Hence, the experimental situation in the VR environment may have been stimulating enough to keep up participants' motivation during a short period of task performance time. It would be interesting to study whether EDA synchrony has long term effect on engaging participants with the task by supporting motivation.

Lastly, we studied whether EDA synchrony occurs during a joint problem-solving task in VR environment without exchange of visual cues. Although the sample in this study was relatively small, both synchrony indices captured significant EDA synchrony in VR environment. This finding indicates that physiological synchrony can occur between dislocated participants in CMC environment and emergence of synchrony is not dependent on visual cues. In addition, although the two synchrony indices stand for markedly disparate methodological approaches, they were codirectional. This finding shows that despite their differences, synchrony could be detected with both methods. It further suggests that despite the fact that synchrony indices used in the field vary to a large extent, the results from different studies are at least partly comparable. However, to build consistent theories, there is an urgent need for standardized ANS synchrony methods

4.1 Limitations and Future Directions

The results of this study reflected the theoretical frameworks, which were built by comparing findings from different experiments. To draw more straightforward conclusions of differences between CMC and face-to-face interactions, the two situations should be studied in the same experiment so that most of the experimental and methodological variation could be controlled. There is a physical, face-to-face version of the collaborative block task used in this experiment, and thus a possibility to study between-group differences during the same tasks exists.

In addition, the analyses of this study were performed using dyadic average empathy, yet there are other ways to indicate group level empathy. For example, our approach does not reveal whether pairwise similarity in empathic skills impact performance. Interestingly, Meslec et al. (2016) evaluated different ways to assess group level RME during collaboration and found that in their study, the lowest individual scores predicted group performance most accurately. In addition, by using linear mixed model methods, group and individual level empathy could be evaluated separately, however conducting these analyses requires a larger sample size than used in this study.

According to previous literature ANS synchrony has been found to emerge independently from context (Palumbo et al., 2017). In this experiment, however, it cannot be fully controlled that physiological synchrony reflects social processes rather than the demands of the shared environment. However, even though ANS synchrony would not be caused by interaction per se, synchrony can reflect shared level of involvement, which may also reveal intriguing aspects of social task engagement. EDA synchrony metrics in this study reflected linear correlational synchrony interpreting that higher synchrony levels provide positive outcomes. Schneider et al. (2020) recently found that EDA synchrony may have time varying components during task performance. Interestingly, they detected moments of high and low synchrony and found that synchrony occurred in cycles, and that cyclic patterns were the most relevant indicators for learning performance and the quality of interaction. Additionally, moments of high synchrony occurred when collaborators were focusing on external events, such as receiving instructions, oscillations in synchrony while interacting, and low synchrony when participants focused on independent work, or were confused.

For support of these findings, Mayo and Gordon (2020) recently introduced a dynamic model which suggests that successful, adaptive interactions consist of moments of synchrony and asynchrony. Group coordination requires an ability to flexibly move in and out of synchrony depending on the task and social context. In addition, their model indicates that during successful interactions, the relation between behavioral and ANS synchrony is adaptively regulated, and therefore different forms of synchrony should be studied independently. The task procedure used in this study differs from Schneider et al. (2020) in task type and duration, and interaction requirements for proceeding in the task. Yet, despite that, to understand the role of EDA synchrony in team dynamics and collaborative success, it would be interesting to study time-varying components of EDA synchrony in more detail.

Studying team physiological dynamics provides potential to advance team theories and create technological design opportunities to support group performance (Kazi et al., 2021). Until recently, ANS synchrony has been studied mostly in a one-dimensional manner, where more synchrony is considered better, and therefore important dynamical aspects of social interaction may yet be fully uncovered. Studies of Schneider et al. (2020) Schneider (2020) and Mayo and Gordon (2020) are another evidence supporting an urgent call for recognizing, contextualizing and specifying patterns of interpersonal synchrony in attempts to understand dynamical, emergent properties of human interaction.

References

Bargh, J. A., McKenna, K. Y. A., and Fitzsimons, G. M. (2002). Can you see the real me? activation and expression of the "true self" on the internet. *Journal of social issues*, 58(1):33–48.

Barsade, S. G. (2002). The ripple effect: Emotional contagion and its influence on group behavior. *Administrative Science Quarterly*, 47:644–675. 0001-8392.

Behrens, F., Snijdewint, J. A., Moulder, R. G., Prochazkova, E., Sjak-Shie, E. E., Boker, S. M., and Kret, M. E. (2020). Physiological synchrony is associated with cooperative success in real-life interactions. *Scientific reports*, 10(1):19609–19609.

Bonfils, K. A., Minor, K. S., Leonhardt, B. L., and Lysaker, P. H. (2018). Metacognitive self-reflectivity moderates the relationship between distress tolerance and empathy in schizophrenia. *Psychiatry research*, 265:1–6.

Cacioppo, J. T., Tassinary, L. G., and Berntson, G. (2001). *Handbook of Psychophysiology.* Cambridge University Press.

Carr, E. W. and Winkielman, P. (2014). When mirroring is both simple and "smart": How mimicry can be embodied, adaptive, and non-representational. *Frontiers in Human Neuroscience*, 8:505.

Carrier, L. M., Spradlin, A., Bunce, J. P., and Rosen, L. D. (2015). Virtual empathy: Positive and negative impacts of going online upon empathy in young adults. *Computers in human behavior*, 52:39–48.

Chanel, G., Kivikangas, J. M., and Ravaja, N. (2012). Physiological compliance for social gaming analysis: Cooperative versus competitive play. *Interacting with computers*, 24(4):306–316.

Chanel, G., Pelli, S., Ravaja, N., and Kuikkaniemi, K. (2010). Social interaction using mobile devices and biofeedback: effects on presence, attraction and emotions.

Chartrand, T. L. and Bargh, J. A. (1999). The chameleon effect: The perception-behavior link and social interaction. *Journal of Personality and Social Psychology*, 76:893–910. 1939-1315.

Chartrand, T. L. and van Baaren, R. (2009). Chapter 5 human mimicry. *Advances in Experimental Social Psychology*, 41:219–274.

Chikersal, P., Tomprou, M., Kim, Y. J., Woolley, A., and Dabbish, L. (2017). Deep structures of collaboration: Physiological correlates of collective intelligence and group satisfaction.

Chrysikou, E. G. and Thompson, W. J. (2015). Assessing cognitive and affective empathy through the interpersonal reactivity index: An argument against a two-factor model. *Assessment*, 23:769–777. doi: 10.1177/1073191115599055.

Coutinho, J., Oliveira-Silva, P., Fernandes, E., Gonçalves, O. F., Correia, D., Perrone McGovern, K., and Tschacher, W. (2019). Psychophysiological synchrony during verbal interaction in romantic relationships. *Family process*, 58(3):716–733.

Cuff, B., Brown, S., Taylor, L., and Howat, D. (2016). Empathy: A review of the concept. *Emotion Review*, 8:144–153. explaining the confusion of consept of empathy.

Curşeu, P. L., Pluut, H., Boroş, S., and Meslec, N. (2015). The magic of collective emotional intelligence in learning groups: No guys needed for the spell. *The British journal of psychology*, 106(2):217–234.

Danyluck, C. and Page-Gould, E. (2019). Social and physiological context can affect the meaning of physiological synchrony. *Scientific Reports*.

Davis, M. H. (1983). Measuring individual differences in empathy: Evidence for a multidimensional approach. *Journal of personality and social psychology*, 44(1):113–126.

de Vignemont, F. and Singer, T. (2006). The empathic brain: how, when and why? *Trends in cognitive sciences*, 10(10):435–441.

de Waal, F. B. and Ferrari, P. F. (2010). Towards a bottom-up perspective on animal and human cognition. *Trends in Cognitive Sciences*, 14:201–207.

Decety, J. and Jackson, P. (2004). The functional architecture of human empathy. *Behavioral and cognitive neuroscience reviews*, 3:71–100.

Decety, J. and Svetlova, M. (2012). Putting together phylogenetic and ontogenetic perspectives on empathy. *Developmental Cognitive Neuroscience*, 2:1–24.

Dindar, M., Järvelä, S., and Haataja, E. (2020). What does physiological synchrony reveal about metacognitive experiences and group performance? *British journal of educational technology*, 51(5):1577–1596.

Dunbar, R. I. and Shultz, S. (2007). Evolution in the social brain. *Science*, 317:1344–1347. 10.1186/1741-7007-5-20.

D'Urso, S. C. and Rains, S. A. (2008). Examining the scope of channel expansion: A test of channel expansion theory with new and traditional communication media. *Management communication quarterly*, 21(4):486–507.

Eisenberg, N. and Eggum, N. D. (2013). Empathic responding: Sympathy and personal distress. *The Social Neuroscience of Empathy*, pages 71–84.

Elkins, A. N., Muth, E. R., Hoover, A. W., Walker, A. D., Carpenter, T. L., and Switzer, F. S. (2009). Physiological compliance and team performance. *Applied ergonomics*, 40(6):997–1003.

Engel, D., Woolley, A. W., Jing, L. X., Chabris, C. F., and Malone, T. W. (2014). Reading the mind in the eyes or reading between the lines? theory of mind predicts collective intelligence equally well online and face-to-face. *PLOS ONE*, 9:e115212.

Feldman, R. (2012). Bio-behavioral synchrony: A model for integrating biological and microsocial behavioral processes in the study of parenting. *Parenting, science and practice*, 12(2-3):154–164.

Feldman, R., Magori-Cohen, R., Galili, G., Singer, M., and Louzoun, Y. (2011). Mother and infant coordinate heart rhythms through episodes of interaction synchrony. *Infant behavior development*, 34(4):569–577.

FeldmanHall, O., Dalgleish, T., Evans, D., and Mobbs, D. (2015). Empathic concern drives costly altruism. *NeuroImage*, 105:347–356. 1053-8119.

Ferrara, E. and Yang, Z. (2015). Measuring emotional contagion in social media. *PloS one*, 10(11):e0142390–e0142390.

Frith, C. D. and Frith, U. (1999). Interacting minds - a biological basis. *Science*, 286:1692–1695. 1095-9203.

Gallagher, H. L. and Frith, C. D. (2003). Functional imaging of ‘theory of mind’. *Trends in Cognitive Sciences*, 7:77–83. 1364-6613.

Gallup, G. G. and Platek, S. M. (2002). Cognitive empathy presupposes self-awareness: Evidence from phylogeny, ontogeny, neuropsychology, and mental illness. *The Behavioral and brain sciences*, 25(1):36–37.

Golland, Y., Arzouan, Y., and Levit-Binnun, N. (2015). The mere co-presence: Synchronization of autonomic signals and emotional responses across co-present individuals not engaged in direct interaction. *PLoS ONE*, 10:e0125804–e0125804. 10.1037/0022-3514.63.2.234.

Gordon, I., Gilboa, A., Cohen, S., Milstein, N., Haimovich, N., Pinhasi, S., and Siegman, S. (2020). Physiological and behavioral synchrony predict group cohesion and performance. *Scientific reports*, 10(1):8484–8484.

Grynberg, D. and López-Pérez, B. (2018). Facing others' misfortune: Personal distress mediates the association between maladaptive emotion regulation and social avoidance. *PloS one*, 13:e0194248–e0194248.

Hannans, J. A., Nevins, C. M., and Jordan, K. (2021). See it, hear it, feel it: embodying a patient experience through immersive virtual reality. *Information and learning science*, 122(7/8):565–583.

Hatfield, E., Cacioppo, J. T., and Rapson, R. L. (1993). Emotional contagion. *Current Directions in Psychological Science*, 2:96–99.

Hein, G. and Singer, T. (2008). I feel how you feel but not always: the empathic brain and its modulation. *Current Opinion in Neurobiology*, 18:153–158.

Henning, R. A., Boucsein, W., and Gil, M. C. (2001). Social-physiological compliance as a determinant of team performance. *International Journal of Psychophysiology*, 40:221–232.

Iacoboni, M. (2009). Imitation, empathy, and mirror neurons. *Annual Review of Psychology*, 60:653–670. doi: 10.1146/annurev.psych.60.110707.163604.

Jiang, L. C., Bazarova, N. N., and Hancock, J. T. (2013). From perception to behavior: Disclosure reciprocity and the intensification of intimacy in computer-mediated communication. *Communication research*, 40(1):125–143.

Järvelä, S., Cowley, B., Salminen, M., Jacucci, G., Hamari, J., and Ravaja, N. (2021). Augmented virtual reality meditation: Shared dyadic biofeedback increases social presence via respiratory synchrony. *ACM transactions on social computing*, 4(2):1–19.

Järvelä, S., Kivikangas, J. M., Kätsyri, J., and Ravaja, N. (2014). Physiological linkage of dyadic gaming experience. *Simulation gaming*, 45(1):24–40.

Järvelä, S., Salminen, M., Ruonala, A., Timonen, J., Mannermaa, K., Ravaja, N., and Jacucci, G. (2019). Dynecom: Augmenting empathy in vr with dyadic synchrony neurofeedback. *Proceedings of the 52nd Hawaii International Conference on System Sciences.*

Karvonen, A., Kykyri, V.-L., Kaartinen, J., Penttonen, M., and Seikkula, J. (2016). *Sympathetic nervous system synchrony between participants of couple therapy*, volume 42.

Kazi, S., Khaleghzadegan, S., Dinh, J. V., Shelhamer, M. J., Sapirstein, A., Goeddel, L. A., Chime, N. O., Salas, E., and Rosen, M. A. (2021). Team physiological dynamics: A critical review. *Human factors*, 63(1):32–65.

Kim, J.-Y. (2000). Social interaction in computer-mediated communication. *Bulletin of the American Society for Information Science and Technology*, 26(3):15–17.

Knight, A. P. and Eisenkraft, N. (2015). Positive is usually good, negative is not always bad: The effects of group affect on social integration and task performance. *Journal of applied psychology*, 100(4):1214–1227.

Kozlowski, S. W. and Ilgen, D. R. (2006). Enhancing the effectiveness of work groups and teams. *Psychological science in the public interest*, 7(3):77–124.

Kramer, A. D. I., Guillory, J. E., and Hancock, J. T. (2014). Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences - PNAS*, 111(24):8788–8790.

Kreibig, S. D. (2010). Autonomic nervous system activity in emotion: A review. *Biological Psychology*, 84:394–421.

Kret, M. E. (2015). Emotional expressions beyond facial muscle actions. a call for studying autonomic signals and their impact on social perception. *Frontiers in Psychology*, 6:711. 10.1111/j.1467-9280.2008.02148.x.

Lakin, J. L. and Chartrand, T. L. (2003). Using nonconscious behavioral mimicry to create affiliation and rapport. *Psychological Science*, 14:334–339. 10.1037/0022-3514.81.6.1014.

Leiberg, S. and Anders, S. (2006). The multiple facets of empathy: a survey of theory and evidence. *Progress in brain research*, 156:419–40.

Levenson, R. W. (2014). The autonomic nervous system and emotion. *Emotion Review*, 6:100–112.

Levenson, R. W. and Ruef, A. M. (1992). Empathy: A physiological substrate. *Journal of personality and social psychology*, 63(2):234–246.

Liu, D., Baumeister, R. F., Yang, C.-c., and Hu, B. (2019). Digital Communication Media Use and Psychological Well-Being: A Meta-Analysis. *Journal of Computer-Mediated Communication*, 24(5):259–273.

Malmberg, J., Järvelä, S., Holappa, J., Haataja, E., Huang, X., and Siipo, A. (2019). Going beyond what is visible: What multichannel data can reveal about interaction in the context of collaborative learning? *Computers in human behavior*, 96:235–245.

Marci, C. D., Ham, J., Moran, E., and Orr, S. P. (2007). Physiologic correlates of perceived therapist empathy and social-emotional process during psychotherapy. *Journal of Nervous and Mental Disease*, 195:103–111. 0022-3018.

Marci, C. D. and Orr, S. P. (2006). The effect of emotional distance on psychophysiologic concordance and perceived empathy between patient and interviewer. *Applied psychophysiology and biofeedback*, 31:115–128.

Mauss, I. B. and Robinson, M. D. (2009). Measures of emotion: A review. *Cognition and Emotion*, 23:209–237.

Mayo, O. and Gordon, I. (2020). In and out of synchrony—behavioral and physiological dynamics of dyadic interpersonal coordination. *Psychophysiology*, 57(6):e13574–n/a.

McLoone, B. and Smead, R. (2014). The ontogeny and evolution of human collaboration. *Biology philosophy*, 29(4):559–576.

Meltzoff, A. N. and Decety, J. (2003). What imitation tells us about social cognition: A rapprochement between developmental psychology and cognitive neuroscience. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 358:491–500.

Meslec, N., Aggarwal, I., and Curseu, P. L. (2016). The insensitive ruins it all: Compositional and compilational influences of social sensitivity on collective intelligence in groups. *Frontiers in psychology*, 7:676–676.

Messina, I., Palmieri, A., Sambin, M., Kleinbub, J. R., Voci, A., and Calvo, V. (2013). Somatic underpinnings of perceived empathy: The importance of psychotherapy training. *Psychotherapy Research*, 23:169–177. 10.1007/s10286-003-0107-5.

Michinov, N., Michinov, E., and Toczek-Capelle, M.-C. (2004). Social identity, group processes, and performance in synchronous computer-mediated communication. *Group dynamics*, 8(1):27–39.

Montague, E., Xu, J., and Chiou, E. (2014). Shared experiences of technology and trust: An experimental study of physiological compliance between active and passive users in technology-mediated collaborative encounters. *IEEE transactions on human-machine systems*, 44(5):614–624.

Mønster, D., Håkonsson, D. D., Eskildsen, J. K., and Wallot, S. (2015). Physiological evidence of interpersonal dynamics in a cooperative production task. *Physiology behavior*, 156:24–34.

Niedenthal, P. M. (2007). Embodying emotion. *Science*, 316:1002 LP – 1005.

Nummenmaa, L., Hirvonen, J., Parkkola, R., and Hietanen, J. K. (2008). Is emotional contagion special? an fmri study on neural systems for affective and cognitive empathy. *NeuroImage (Orlando, Fla.)*, 43:571–580.

Oliveira-Silva, P. and Gonçalves, F. (2011). Responding empathically: A question of heart, not a question of skin. *Applied psychophysiology and biofeedback*, 36(3):201–207.

Oveis, C., Horberg, E. J., and Keltner, D. (2010). Compassion, pride, and social intuitions of self-other similarity. *Journal of personality and social psychology*, 98(4):618–630.

Palumbo, R. V., Marraccini, M. E., Weyandt, L. L., Wilder-Smith, O., McGee, H. A., Liu, S., and Goodwin, M. S. (2017). Interpersonal autonomic physiology: A systematic review of the literature. *Personality Social Psychology Review (Sage Publications Inc.)*, 21:99–141.

Powell, P. A. and Roberts, J. (2017). Situational determinants of cognitive, affective, and compassionate empathy in naturalistic digital interactions. *Computers in human behavior*, 68:137–148.

Praszkier, R. (2014). Empathy, mirror neurons and sync. *Mind society*, 15(1):1–25.

Preston, S. D. and Hofelich, A. J. (2012). The many faces of empathy: Parsing empathic phenomena through a proximate, dynamic-systems view of representing the other in the self. *Emotion Review*, 4:24–33. doi: 10.1177/1754073911421378.

Prochazkova, E. and Kret, M. E. (2017). Connecting minds and sharing emotions through mimicry: A neurocognitive model of emotional contagion. *Neuroscience and Biobehavioral Reviews*, 80:99–114.

Páez, D., Rimé, B., Basabe, N., Wlodarczyk, A., and Zumeta, L. (2015). Psychosocial effects of perceived emotional synchrony in collective gatherings. *Journal of personality and social psychology*, 108(5):711–729.

Rizzolatti, G. and Craighero, L. (2004). The mirror-neuron system. *Annual Review of Neuroscience*, 27:169–192. doi: 10.1146/annurev.neuro.27.070203.144230.

Salminen, M., Jarvela, S., Ruonala, A., Harjunen, V., Jacucci, G., Hamari, J., and Ravaja, N. (2019). Evoking physiological synchrony and empathy using social vr with biofeedback. *IEEE transactions on affective computing*, pages 1–1.

Schneider, B., Dich, Y., and Radu, I. (2020). Unpacking the relationship between existing and new measures of physiological synchrony and collaborative learning: a mixed methods study. *International journal of computer-supported collaborative learning*, 15(1):89–113.

Schnell, K., Bluschke, S., Konradt, B., and Walter, H. (2011). Functional relations of empathy and mentalizing: An fmri study on the neural basis of cognitive empathy. *NeuroImage*, 54:1743–1754. Copyright - Copyright Elsevier Limited Jan 15, 2011

Last updated - 2015-04-06.

Shamay-Tsoory, S. G., Saporta, N., Marton-Alper, I. Z., and Gvirts, H. Z. (2019). Herding brains: A core neural mechanism for social alignment. *Trends in Cognitive Sciences*, 23:174–186. 1364-6613.

Shin, D. (2018). Empathy and embodied experience in virtual environment: To what extent can virtual reality stimulate empathy and embodied experience? *Computers in human behavior*, 78:64–73.

Stel, M., Blascovich, J., McCall, C., Mastop, J., van Baaren, R. B., and Vonk, R. (2010). Mimicking disliked others: Effects of a priori liking on the mimicry-liking link. *European journal of social psychology*, 40(5):867–880.

Stürmer, S., Snyder, M., Kropp, A., and Siem, B. (2006). Empathy-motivated helping: The moderating role of group membership. *Personality social psychology bulletin*, 32(7):943–956.

Syrjämäki, A. H., Isokoski, P., Surakka, V., Pasanen, T. P., and Hietanen, J. K. (2020). Eye contact in virtual reality – a psychophysiological study. *Computers in human behavior*, 112:106454–.

Tidwell, L. C. and Walther, T. B. (2002). Computer-mediated communication effects on disclosure, impressions, and interpersonal evaluations: Getting to know one another a bit at a time. *Human communication research*, 28(3):317–348.

Tomasello, M., Melis, A. P., Tennie, C., Wyman, E., and Herrmann, E. (2012). Two key steps in the evolution of human cooperation: The interdependence hypothesis. *Current anthropology*, 53(6):673–692.

Tomprou, M., Kim, Y. J., Chikersal, P., Woolley, A. W., and Dabbish, L. A. (2021). Speaking out of turn: How video conferencing reduces vocal synchrony and collective intelligence. *PLOS ONE*, 16:e0247655.

Venkatesh, V. and Windeler, J. B. (2012). Hype or help? a longitudinal field study of virtual world use for team collaboration. *J. Assoc. Inf. Syst.*, 13:5.

Ventura, S., Cardenas, G., Miragall, M., Riva, G., and Baños, R. (2021). How does it feel to be a woman victim of sexual harassment? the effect of 360°-video-based virtual reality on empathy and related variables. *Cyberpsychology, behavior and social networking*, 24(4):258–266.

Victor, J. and Dilorenzo, P. (2013). *Statistical Identication of Synchronous Spiking*. CRC Press.

Waal, F. B. D. (2008). Putting the altruism back into altruism: The evolution of empathy. *Annual Review of Psychology*, 59:279–300. 1545-2085.

Waal, F. B. D. and Preston, S. D. (2017). Mammalian empathy: Behavioural manifestations and neural basis. *Nature Reviews Neuroscience*, 18:498–509.

Walther, J. B. (1992). Interpersonal effects in computer-mediated interaction: A relational perspective. *Communication Research*, 19(1):52–90.

Wechsler, D. (1955). Wechsler adult intelligence scale–. *Archives of Clinical Neuropsychology*.

Wikström, V., Martikainen, S., Falcon, M., Ruistola, J., and Saarikivi, K. (2020). Collaborative block design task for assessing pair performance in virtual reality and reality. *Heliyon*, 6(9):e04823–e04823.

Wiltermuth, S. S. and Heath, C. (2009). Synchrony and cooperation. *Psychological science*, 20(1):1–5.

Wood, A., Rychlowska, M., Korb, S., and Niedenthal, P. (2016). Fashioning the face: Sensorimotor simulation contributes to facial expression recognition. *Trends in Cognitive Sciences*, 20:227–240.

Woolley, A. W., Aggarwal, I., and Malone, T. W. (2015). Collective intelligence and group performance. *Current directions in psychological science : a journal of the American Psychological Society*, 24(6):420–424.

Woolley, A. W., Chabris, C. F., Pentland, A., Hashmi, N., and Malone, T. W. (2010). Evidence for a collective intelligence factor in the performance of human groups. *Science*, 330:686 LP – 688.

Zahn-Waxler, C. and Radke-Yarrow, M. (1990). The origins of empathic concern. *Motivation and Emotion*, 14:107–130.

Zahn-Waxler, C., Radke-Yarrow, M., Wagner, E., and Chapman, M. (1992). Development of concern for others. *Developmental Psychology*, 28:126–136. 1939-0599.

Ziegler, J. C., Montant, M., Briesemeister, B. B., Brink, T. T., Wicker, B., Ponz, A., Bonnard, M., Jacobs, A. M., and Braun, M. (2018). Do words stink? neural reuse as a principle for understanding emotions in reading. *Journal of cognitive neuroscience*, 30(7):1023–1032.