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Interpersonal Nonverbal Movement Synchrony in Parent-Child Dyads: Analysing Play Procedures using the NICE Toolbox

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1. Abstract

Interpersonal temporal coordination refers to the alignment of bodily signals between two individuals in rhythmically matched or predictably coupled patterns during joint activity. Movement synchrony is the observable expression of interpersonal temporal coordination. It is considered a fundamental component of effective communication, emotional attunement, and shared attention. In parent–child interactions, movement synchrony provides insight into how body movement supports and reflects the quality of communication across different social contexts. To quantify these processes, the present study uses the Nonverbal Interpersonal Communication Exploration (NICE) Toolbox, which includes automated, video-based pose estimation algorithms, which analyse naturalistic interactions in both free play and structured play conditions in parent-child dyads. Sixteen parent–child dyads with children aged 4 to 10 were recruited from the university's psychotherapeutic outpatient clinic. Each dyad completed two standardized play situations: a free play interaction and a structured play task (approximately 5–7 minutes each). In total, 32 videos were analysed using the NICE Toolbox, which extracted frame-by-frame movement data using ViTPose, a pose estimation algorithm. Subsequently, we calculated synchrony indices using windowed cross-correlation analysis. To further assess ecological validity and determine whether observed synchrony reflected genuine coordination rather than chance-level covariation, synchrony indices were compared with pseudosynchrony baselines generated through the Surrogate Synchrony (SUSY) framework. We found that observed synchrony levels were significantly higher than pseudosynchrony levels across dyads, indicating that parent–child movement coordination occurred at above-chance levels and reflected true interactive coupling. However, we were not able to find a significant difference between the play contexts. Nonetheless, the descriptives and visualization suggested that there was a slight variation depending on the play context with free play showing slightly higher variability compared to structured play. This study validates the NICE Toolbox as a reliable and scalable method for quantifying movement coordination in naturalistic settings. Furthermore, the findings highlight movement synchrony as a measurable marker of interaction quality in the context of developmental and clinical psychology research and demonstrates its potential to connect moment-to-moment coordination with broader aspects of relational functioning in naturalistic interactions.

Keywords: Temporal Coordination, Movement Synchrony, Parent-Child Interaction, Body Pose Estimation, NICE Toolbox.

2. Introduction

2.1 Interactions in Early Development

Human development unfolds through social interactions that take place in the earliest stages of life (Feldmann, 2007). Through childhood, children engage with their caregivers in continuous exchanges that pillar behavioral, physiological, and neural regulation which form the foundation for a child's developmental trajectory (Feldmann, 2007). Children actively participate in interactions that go on to shape their developmental capacities across various cognitive, emotional, and social domains (Gauvain, 2001). Such interactions in a child's early life can provide them with an environment which is either guided or constrained by the level of responsiveness shown by their social partner, often a caregiver or parent (Galasyuk & Mitina, 2020).

Hornbæk & Oulasvirta (2017) define an interaction as the situated, embodied engagement of a person with their environment and tools, shaped by intention, context and the coupling of actions. Early interactions that take place between the parent and the child play a pivotal role in development, as parents often serve as children's primary sources of stimulation, support and regulation (Dozier et al., 2013). Offering cues that guide attention, scaffold learning, and harmonize emotional states, parents help construct their child's experiences from the ground up (Milteer et al., 2012). Research has suggested that sensitive and responsive caregiving carves a path for children to be able to regulate arousal and emotion (Lobo et al., 2026). Similarly, strong interactive routines like play and turn-taking drive early learning and social understanding between the caregiver-child dyad (Lourenço et al., 2023). Bowlby (2012) proposed that over consecutive years of development, these interactive routines can help form secure relationships, providing a secure base for trust and positive relationships.

The effectiveness of such interactions isn't determined singularly by these behaviours, rather multiplied through coordinated dynamic behaviours over time (Cornejo et al., 2017). Interactions are known to be reactive, reciprocal processes where children and caregivers continuously adjust to each other's body movement, facial expressions and momentary actions (Legerstee, 2009). Defined as temporal organization, it allows interactions to not only be apathetic but energetic, vibrant and robust (Dale et al., 2013). Constantly shifting and evolving, allowing both partners to anticipate, respond and adapt in ways that maintain mutual understanding going beyond verbal communication (Dale et al, 2013). This temporal organization and coordination is a core property of early social development allowing for parents and children to develop their inter-dependent ways of emotional regulation, learning and bonding (Carollo et al., 2021). This dynamic nature of early development is the root of how two systems, the parent and the child, coordinate their behaviour in time, synchronizing their emotional and behavioral rhythms (Markova et al., 2019).

2.2 Interpersonal Synchrony and Temporal Coordination

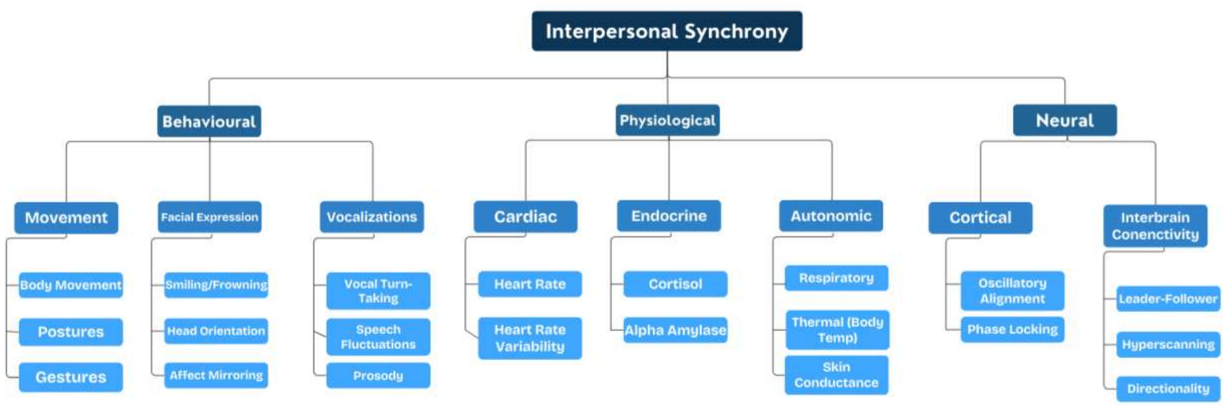
This form of attunement between two interacting systems, in this case parent and child, is defined as temporal coordination (Wilcox et al., 2025). Feldmann (2007) defines this as the coordination of micro-level social behaviour, where parent-infant synchrony refers to the matching of behaviour during a social interaction which exceeds chance, highlighting the reciprocal influence between two interacting partners. Temporal coordination can develop through multiple facets, one of them being interpersonal synchrony (Feldmann, 2007). Interpersonal synchrony is when two individuals form a systematic alignment by coupling their behaviours, physiology and neural networks during an interaction (Harrist & Waugh, 2002). As opposed to them responding to each other in a solitary manner, interpersonal synchrony allows for two systems to be temporally connected, such that one system's changes relate to changes in another (Sfeir et al., 2025). This alignment may take place simultaneously or with a time lag, often reflecting ongoing adaptation of one system to the other during an interaction (Ramseyer, 2008).

Synchrony can be understood as a prominent manifestation of temporal coordination highlighting the dynamic relationship between two interacting systems (Feldmann, 2007). This allows the caregiver and the child to intertwine their personal autonomous systems to their own rhythms, which then aligns and readjusts dynamically through reciprocated influence of one system to the other (Leclère et al., 2014). Mayo & Gordon (2020) proposed that synchrony develops when the temporal structure of one partner corresponds with that of another, forming patterns which go beyond chance and coincidence. This doesn't always mean perfect alignment of behaviour, rather it reflects flexible coordination which allows both partners to maintain their level of engagement while responding to new signals during the interaction (Mayo & Gordon, 2020).

In parent-child interactions, interpersonal synchrony plays a crucial role in withholding or guiding developmental processes (Feldmann, 2007). Feldmann (2017) put forth the idea that higher level emotions such as affect and arousal, are often maneuvered by the ability to temporally coordinate, allowing two systems to successfully co-regulate as one, rather than two independent systems. In a parent-child dynamic, interpersonal synchrony can allow the child to learn through interactions, as coordinated timing of behaviour can enhance a child's ability to attend to and predict the caregiver's behaviour (Harrist & Waugh, 2002). This creates a supportive environment for them to explore and acquire unique skills which can only be learned by continuous, time-specific interactions (Harrist & Waugh, 2002). This level of synchrony, when achieved through a multitude of interactions over a period of time, can allow for the development of attachment bonds (Isabella & Belsky, 1991). In turn, such attachment bonds reinforce a sense of mutual engagement and connectedness between the child and the parent (Isabella & Belsky, 1991). Hence, interpersonal synchrony can serve as a core organizing principle in early interactions, aligning caregiver-child behaviour, laying the foundation for a wide range of developmental outcomes.

Figure 1

Typically Known Modalities of Interpersonal Synchrony: Behavioral; Physiological & Neural.



2.3 A Deep Dive into Interpersonal Synchrony: Movement Synchrony

Synchrony via temporal organization during an interaction can be observed across varying modalities (Sfeir et al., 2025). In parent-child interaction research, it is common to observe synchrony through behavioral domains such as gaze, vocalizations, affect, facial expressions, as well as physiological processes such as heart rate variability (HRV), cortisol activity, changes in body temperatures and through hyperscanning neural activity monitored by electroencephalography (EEG) or functional near-infrared spectroscopy (fNIRS) (Feldmann, 2007; Feldmann et al., 2011; Pili et al, 2025). By analysing synchrony across these domains, researchers are able to grasp the extent to which adjustments in one partner's behavioral state can affect the other's ability to mirror or regulate such changes in behaviour (Wilcox et al., 2025). This emphasizes the multi-faceted nature of coordinated interactions which are powered by synchronized shuffling of behavioral outcomes during the interaction (Ohayon & Gordon, 2025).

Movement synchrony, within the behavioral domain is one such example of a modality with which synchrony can be observed (Lakens, 2010). An expression of interpersonal coordination, body movement serves as a continuous, ever-evolving, dynamic signal that unfolds over time and reflects ongoing engagement between two systems (Schmidt & Richardson, 2008). Discrete behaviours such as gaze shifts, facial expressions and gestures are forms of movement which are present throughout an interaction (Richardson et al., 2008). They allow researchers to be able to observe the level of coordination at very minute, fine grained temporal scales (Paxton & Dale, 2013). Since movement is very closely intertwined with attention, affect and action, patterns of coordinated movement can help offer detailed insight into how two or more interacting systems may evolve and adapt to one another in real time, also sometimes without conscious awareness (Keller et al., 2014).

Early research on movement-based coordination has demonstrated that two more interacting individuals tend to spontaneously align their movements during social engagement (Galotti et al., 2017). Research in both adult and child domains suggest that coordinated body movement can emerge naturally during interaction (Koul et al., 2023; Cornejo et al., 2024). This is done by reflecting or mirroring shared rhythms, almost like a dance which takes mutual influence and isn't intentional mimicry of one's actions (Keller et al., 2014). In a parent-child context, this temporal organization of movement is linked to engagement quality and interactional attunement, suggesting that movement synchrony may serve as an additional building block through which temporal coordination can be expressed during an interaction (Wilcox et al., 2025). This research has motivated an ever-growing interest in studying movement synchrony as a window into the dynamics of social interactions, underlining the need for reliable methods to capture coordination between bodies over time.

2.4 Nonverbal Synchrony and Body Movement

A major part of social interaction in the early stages of development is conveyed through nonverbal communication (Hall et al., 2019). In early life, infants often rely on bodily cues such as posture, gesture, facial expression and movement to understand signals by their caregiver (Papoušek, 2007). Growing up into childhood, these cues manifest and form deeper connections to serve a purpose of communication that goes hand-in-hand with verbal communication (Cochet & Bryne, 2016). Caregivers then respond to these cues through their own nonverbal behaviours forming a rich collection of embodied signals which are exchanged and recreated over time as the bond between the caregiver and child grows deeper over time (van der Klis et al., 2023). In most cases, such nonverbal cues form the primary medium through which early social coordination takes place, making it a critical focus for understanding a caregiver-child interaction.

One such component of nonverbal communication is synchronized body movement which expands and unfolds continuously throughout interaction and reflects the ongoing engagement between the two systems (Tsuchiya et al., 2020). Body movement such as shifts in posture, organized gesturing, rhythmic pattern and leader-follower dynamics are not just isolated events, but rather a part of a dynamic stream of changes and adjustments that evolve over time (Dale et al., 2020). This kind of body movement, which is inherently temporal, provides a natural glance into how two interacting partners coordinate their behaviour moment by moment (Keller et al., 2014). This synchronization of movement within this framework allows us to capture the exact degree to which the temporal structure of one's movements reorganizes with regards to the other, indicating the coordination between two systems (Koul et al., 2023).

Studying interaction at the early stages of human development can often be tricky (Leclère et al., 2014). Hence, focusing on movement-based synchrony offers several advantages for the study of early interactions (Hoch et al., 2022). Firstly, movement is a continuous signal that can be examined at each minute detail in a frame-by-frame manner at fine temporal resolutions with regards to video analyses. This allows researchers to capture subtle patterns of coordination that may be ignored in an event-based measure (Ramseyer, 2013). Secondly, movement-based approaches are natural and often unconscious, making them less reliant on subjective coding of discrete behaviours such as gaze, affect or vocalizations (Koul et al., 2023). This offers a greater potential for objectivity and reproducibility. Additionally, due to the implicit nature of movement coordination, often without conscious awareness of explicit instruction, it has the tendency to reflect fundamental interactional processes which operate beneath the more overt communicative behaviours (Keller et al., 2014). Collectively, these advantages allow movement synchrony to be strongly poised as one of the more powerful indicators of temporal coordination in caregiver-child interactions highlighting the importance of producing robust methods to measure this coordination between two bodies over time (Ramseyer & Tschacher, 2011).

2.5 Measuring Nonverbal Movement Synchrony: Motion Energy Analysis

Condon and Ogston (1966) first described this form of nonverbal communication as ‘nonverbal synchrony’. They coined the term as a phenomenon describing coordinated movement between interacting individuals as ‘interactional synchrony’ (Condon & Ogston, 1966). Ramseyer & Tschacher (2011) then further conceptualized ‘nonverbal synchrony’ as a phenomenon having three distinguished features. Firstly, it has a dynamic quality. Secondly, it can be measured objectively and automatically by a video-computer interface and lastly, it has evident simultaneous movement (Codon & Ogston, 1966) as well as a ± 5 second window of time-lagged coordinated movement. As Ramseyer & Tschacher (2011) suggested, a core challenge of studying interpersonal coordination such as nonverbal synchrony lies in highlighting the possible functional methods which are capable of capturing how two or more interacting individuals move together across time.

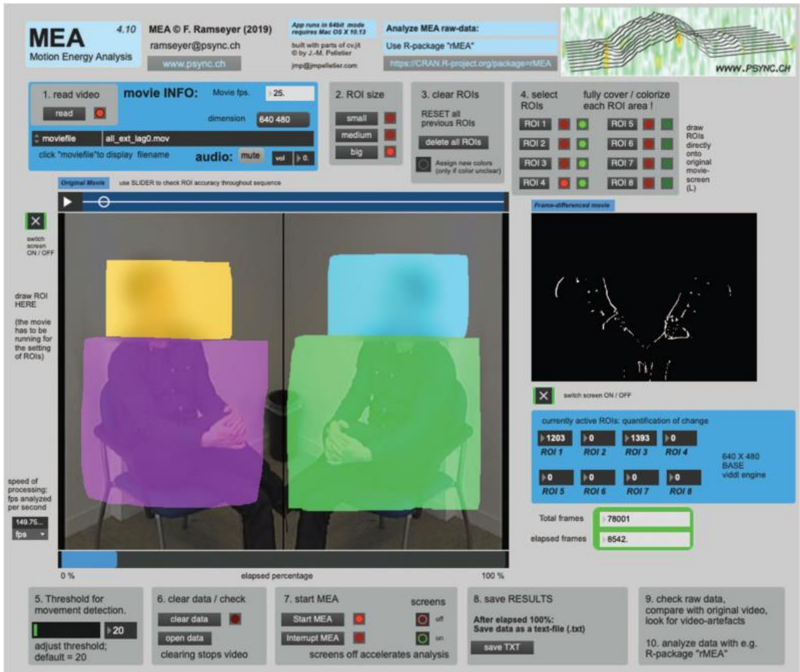
In the early 2000s, as the interest in studying movement synchrony grew, several methods were developed as a way to quantify nonverbal synchrony using a video-based computer analysis Ramseyer & Tschacher (2011) identified such methods as essential to study this type of temporal coordination. Among them, Motion Energy Analysis (MEA), developed by Fabian T. Ramseyer & Wolfgang Tschacher at the University of Bern, emerged as a widely used software for measuring nonverbal behavioral coupling. They used MEA in their first publication in 2008 and further formalized it through more research in 2011.

Ramseyer & Tschacher (2011) used the MEA software to study nonverbal synchrony during psychotherapy sessions. They aimed to study whether movement synchrony between patients and therapists could be objectively detected and related to the outcomes of the therapy sessions. They used MEA on 104 videotaped sessions and were able to find that that real patient-therapist dyads presented a significantly higher level of synchrony as compared to shuffled pseudodyads, reaffirming that synchrony present in two interacting individuals reflects interpersonal coupling rather than by-chance coupling. They were able to conclude that higher synchrony predicted stronger therapeutic alliance, greater engagement between patient and therapist and moreover, a larger reduction in symptoms, showcasing nonverbal synchrony as a meaningful indicator of therapeutic progress.

The Motion Energy Analysis software quantifies movement by examining changes in pixel intensity across video frames within predefined regions of interests (ROIs) drawn out by the researcher (*see Fig.1 below*). Each frame of the video is then compared to the next one, producing a time series of 'motion energy' representing the degree of movement shown at each point in time. Every subtle variation from frame to frame can then be tracked by the researchers in movement over milliseconds with each frame providing a high-resolution representation of how two interacting partners' dynamic movement fluctuates and coordinates during an interaction. Once the motion energy time series data are extracted for both individuals, synchrony is quantified statistically. Commonly, this is done via windowed cross-correlation analyses, allowing researchers to examine the alignment of movement patterns between two individuals across varying time lags (cross-correlation) and also compare fluctuations in the level of synchrony across the interaction (windowed analyses). Studying these patterns can help reveal the degree of temporal coordination between individuals evident when their movements are aligned and also examine whether one partner tends to lead or follow in the interaction.

Figure 2

An Illustrative Example of the Motion Energy Analysis Software Demonstrating How Raw Video Footage Is Processed (Ramseyer, 2011)



Note**:** The colours represent the Regions of Interest drawn by the researcher (Ramseyer, 2011)

The major advantage of using MEA as a method to study nonverbal synchrony is its ability to detect subtle moment-to-moment movement coordination which is often difficult to capture through traditional observational coding. Human-based coding measures can often prove to have biases especially when examining minute behavioral changes in an interaction. They can also be time-consuming and subjective. MEA is able to work through these limitations as it provides researchers with objective, continuous data. MEA is especially valuable when studying naturalistic settings such as patient-therapist, parent-child or social learning contexts. In addition to being cost-effective and minimally labor-intensive, MEA is easy to use and requires little to no specialized training allowing researchers and even students to become proficient at it without requiring extensive coding expertise. Most importantly, when studying parent-child interactions, it proves to be a non-intrusive method to study synchrony, enabling the observation of spontaneous coordination without disrupting the participants' behaviour or flow of interaction. Moreover, MEA is highly ecologically valid due to its ability to capture movement as a continuous signal at a high-resolution frame-by-frame manner rather than requiring specialized motion-capture equipment (Paxton & Dale, 2013). Moreover, by producing time series data, MEA enables researchers to apply a wide range of statistical analyses such as cross-correlation and windowed correlation to examine not only whether participants move together, but also how synchrony fluctuates over time and whether one participant tends to lead or follow. This combination of precision, objectivity, ease of use, and flexibility makes MEA a uniquely powerful tool for exploring the dynamic structure of social interactions in ways that were previously inaccessible.

Due to MEA being an easy-to-use software, it has been adopted by multiple researchers. However, it has its own limitations underlined by developers Ramseyer and Tschacher (2020). Regardless of the quality or suitability of the video material, MEA quantifies movement by studying the change in pixel rate in a frame-by-frame manner. This means that certain recordings with unstable cameras or changing backgrounds or poor lighting can produce a result that can contain artefacts. The authors recommend that to avoid these risks it is important to maintain consistency in the camera, background and lighting settings across the interaction. Secondly, when choosing the predefined ROIs, MEA isn't able to assess the quality or direction of the movement, hence, it cannot distinguish between posture shifts vs. gestures or head movement vs foot movement. This issue can be addressed by having multiple ROIs, however MEA isn't able to dynamically adjust ROIs according to movement patterns. Lastly, a key limitation of MEA arises when individuals in the frame overlap. For example, when a child leans into a parent's lap. As mentioned earlier, MEA measures pixel intensity within predefined ROIs, therefore, when two individuals overlap the signal can be confounded. This makes it impossible to know who is producing which movement. This can cause ambiguous synchrony measures as movement from one individual can be incorrectly attributed to the other. Moreover, MEA is also unable to separate intertwined body parts, causing joint movement to be treated as a single combined signal rather than movement coordinated by two individuals. Hence, analysis of situations with overlapping participants should be interpreted with caution and ROIs must be placed carefully keeping in mind stable camera angles, backgrounds and lighting to ensure accurate data collection.

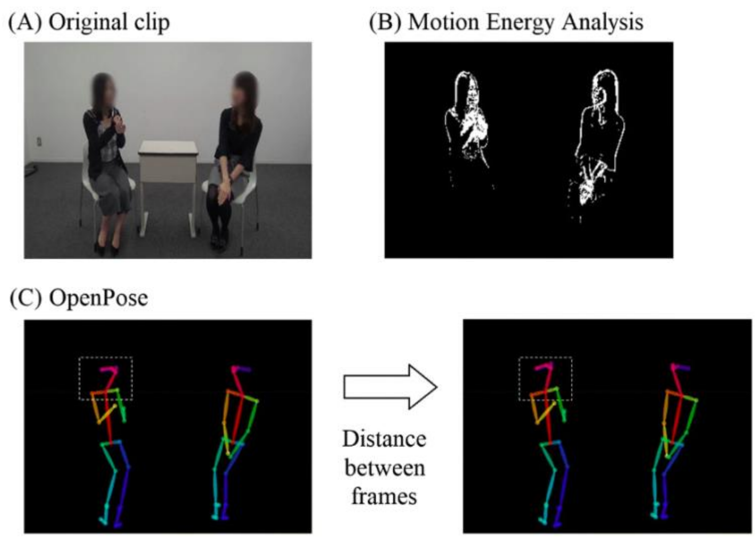
2.6 Advancing Movement Measurement: Body Pose Estimation

To overcome the limitations of the Motion Energy Analysis (MEA) software, researchers have turned to the use of body pose estimation approaches . Body pose estimation is a computer based vision technique which allows scientists to track the position and orientation of key body parts, such as, the head, torso, arms, legs etc. This technique allows us to form a map of these structural points into a skeletal representation of the body allowing researchers to automatically analyse how a person moves, gestures, or interacts with others in real time (Tharatipayakul et al., 2024). Body pose estimation uses machine learning models to track anatomical landmarks across time, creating a time series of joint coordinates that represent the positioning of each body part in every video frame (Tharatipayakul et al., 2024). This method allows researchers to be able to interpret movement kinematics (Cao et al., 2021). Movement kinematics is the study of human motion in terms of spatial and temporal characteristics, this includes body positioning, velocity and acceleration, without considering the forces that cause that movement (Abernethy et al., 2013). *Movement kinematics* are a major aspect of understanding temporal coordination manifested as nonverbal synchrony (Koul et al., 2023). For example, OpenPose is a multi-person 2D pose estimation framework which extracts keypoint body data across frames (Cao et al., 2021).

Grinspun et al. (2024) used OpenPose estimation to analyse joint movement in a mother-child dyad during a dance task. They were able to find that a comparatively simple measure of synchrony, head movement coherence, was significantly correlated to observational interaction quality scores, proposing that computational synchrony metrics can serve as valid indicators of the quality of naturalistic dyadic interactions. Interestingly, Diaz-Rojaz & Myowa (2024) recognized that OpenPose is a valuable tool to study naturalistic dyadic interactions, however, the infant tracking remains challenging. Therefore, they developed a 3D parent-infant pose estimation system using Azure Kinect and OpenPose to study developmental interactions allowing them to capture valuable kinematic data. Complementing these advances in kinematic movement data collection, Efthimiou and Crompton (2025) introduced duet, an open-source R package that streamlined the processing of large volumes of OpenPose motion data for dyadic interaction research. Duet is able to automate JSON consolidation, kinematic computation, interpolation, motion energy extraction, synchrony estimation, making pose-based, detailed movement analysis more accessible and scalable for researchers studying coordination in social interactions. The aforementioned methodological advancements in studying movement kinematics suggest that precise, automated tracking of movement can provide new insights into the dynamics of dyadic interactions in naturalistic settings. Body pose estimation allows scientists to study movement kinematics across time, presenting patterns of coordination which are difficult to measure with traditional coding or pixel-based approaches like MEA.

Figure 3

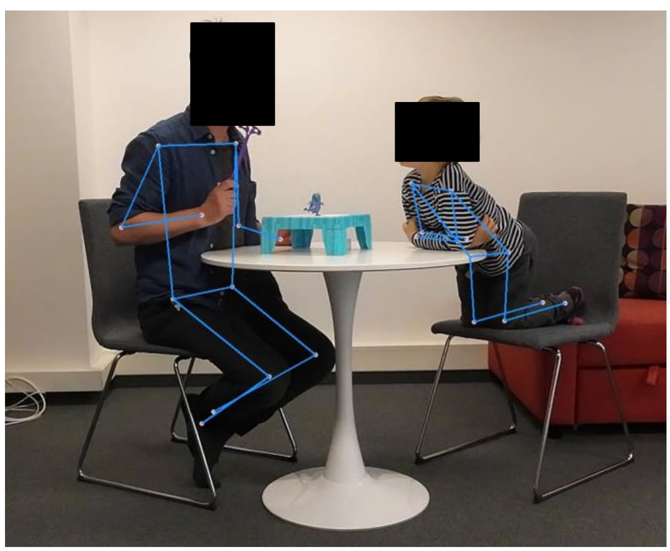
Illustrative Example Comparing Outputs of the Pixel-Based Motion Energy Analysis (B) and OpenPose Using Body Pose Estimation (C) (Fujiwara & Yokomitsu, 2021)



This thesis will use a novel development, *The Nonverbal Interpersonal Communication Exploration* (NICE) Toolbox developed by Schmitt et al. (2025) at the Max Planck Institute for Intelligent Systems at the University of Tübingen is one such example of a Toolbox which uses body pose estimation for studying dyadic interactions in a naturalistic setting. The NICE Toolbox is an open-source framework which was designed to analyse nonverbal communication from single or multi-camera video data. It is a state-of-the-art computer vision software that uses deep learning building upon a framework that consists of a collection of different computer vision algorithms converting them into a single, transparent pipeline allowing the extraction of multiple nonverbal movement signals which are relevant to social, naturalistic interactions. The toolbox includes invaluable variables such as whole-body pose using body joints, hand and facial landmarks, gaze direction, head orientation, interpersonal distance, movement kinematics and emotional expressions. Using body pose estimation, the software identifies 2D, x and y coordinates of key body joints (e.g., shoulders, elbows, hips, wrists, and ankles) along with confidence scores of each joint, i.e., how confident the software is for each joint from a scale of 0 to 1. In order to achieve high accuracy in full-body joint detection, the NICE Toolbox uses ViTPose, a transformer-based algorithm that functions by modeling long-range spatial relationships with each body part (Xu et al., 2022). Each body joint, in each frame, serves as a data point which is post-processed through filtering to reduce noise, after which movement dynamics, i.e., kinematic displacement and velocity of each joint is computed. This allows the NICE toolbox to be a transparent and extensible framework for studying nonverbal behaviour and interpersonal coordination over time. The implementation and adaptation of the NICE Toolbox will be further explained in the ***Methods*** section.

Figure 4

An Example of a Frame from the NICE Toolbox Software Demonstrating How Raw Video Footage Looks After a Video is Processed.



2.7 The Present Study

Nonverbal interpersonal synchrony can manifest as a form of temporal coordination between two interacting individuals across developmental research (Ramseyer & Tschacher, 2011). It is a foundational mechanism through which parent-child interactions aid emotional regulation, learning and social bonding (Lobo et al., 2026). As mentioned before, synchrony is a dynamic phenomenon which presents itself during interactions through physiological, neural and behavioral channels (Feldmann, 2007; Feldmann et al., 2011; Pili et al, 2025). One such behavioral channel, nonverbal movement synchrony offers a continuous and implicit glimpse of how two systems align themselves across time (Leclère et al., 2014). Observing and analysing this phenomenon can be performed via traditional behavioral coding and computerized pixel-based approaches such as Motion Energy Analysis (Ramseyer & Tschacher, 2011). Nonetheless, these methods remain constrained by certain limitations, such as biases, interpretability, transparency and most importantly, precision in detecting the source of movement. This presents us with meaningful gaps in movement synchrony research which can be addressed by using other methodological approaches such as body pose estimation, more specifically the ViTPose algorithm in the NICE Toolbox (Schmitt et al., 2025). Despite the rising interest amongst researchers in quantifying synchrony, true empirical research applying modern body pose-based methods in a naturalistic parent-child scenario remains limited. A substantial body of literature now demonstrates that synchrony both exists and matters. However, knowledge on how synchrony unfolds during naturalistic interactions, particularly in parent-child interactions remains understudied. Advancing research in this direction will not only deepen our understanding of children's developmental foundations but also help us refine therapeutic approaches.

The present study aims to examine this gap in nonverbal movement synchrony research by observing parent-child play scenarios. Parent-child play situations provide us with a rich, highly naturalistic outlook into continuous and spontaneous temporal coordination (Kidby et al., 2023). Play situations can be a developmentally enriching perspective which can allow both parent and child to co-create and co-regulate without experimental constraints (Kidby et al., 2023). This allows for play contexts to be an ideal method to observe the dynamic nature of behavioral alignment between parent and child. Vygotsky (1967) believed that through play children are able to use their ingenuity to create imaginary events that originate from real live circumstances. Saracho (1998) further proposed that play can be studied through free play, structured play and semi-structured play. Free play is navigated by the child, often spontaneous and supports individuality, creativity and is a natural way of expressing behaviour (Pellegrini & Smith, 1998)2. Structured play is often navigated by the adult, including predefined instructions that shape behaviour towards a shared outcome (Fisher et al., 2008). Ultimately, semi-structured play blends the two extremes through scaffolding behaviour while allowing the child to also take initiative as the adult guides play towards a shared outcome (Vygotsky, 1978). The current study uses both structured and free play situations to examine how nonverbal movement synchrony manifests itself in both varying scenarios. The free play scenario can allow us to capture natural, self-generated patterns of interaction whereas the structured play context can provide us with a comparative under shared instructions and goals allowing synchrony to manifest across two varying naturalistic contexts (Krijnen et al, 2023).

The present study aims to address some key objectives. Firstly, we aim to explore the validity and reliability of the novel NICE Toolbox and its ability to assess nonverbal movement in naturalistic parent-child interactions by applying ViTPose, a pose-estimation-based algorithm that captures full body motion with precision and transparency. Secondly, we aim to observe whether observed dyadic interactional synchrony exceeds what would be expected by chance, or pseudosynchrony. Lastly, we aim to explore how movement synchrony differs between free play and structured play context.

2.8 Research Question & Hypotheses

Under the umbrella of the aforementioned objectives, the study aims to answer three questions:

Q1. To what extent can the NICE Toolbox reliably capture patterns of nonverbal movement synchrony in parent-child dyads during naturalistic interactions?

Q2. How does nonverbal movement synchrony manifest as temporal coordination during naturalistic parent–child interactions (free play vs. structured play), and does observed synchrony significantly exceed pseudosynchrony (i.e., synchrony expected by chance)?

Q3. Does movement synchrony differ between free play and structured play conditions?

Based on these objectives and research questions, as well as the existing literature on parent-child movement synchrony, the following hypotheses were formulated to examine expected patterns of coordination and the performance of the NICE Toolbox. Keeping in mind that the NICE Toolbox is a novel development along with the foundation laid by previous research on interpersonal synchrony in parent-child dyads (e.g., Ramseyer & Tschacher, 2011; Delaherche et al., 2012) allow us to posit the following hypotheses:

RQ1-H1. Due to theoretical advantages the NICE Toolbox offers over other traditional measures, it could prove to be useful to study movement kinematics in future studies, however due to the exploratory nature of this study, examining the NICE Toolbox for the first time, no formal hypothesis can be made at this stage.

RQ2-H2. The dyads will display movement coordination that exceeds chance, or pseudosynchrony levels (e.g., Ramseyer & Tschacher, 2011; Delaherche et al., 2012).

RQ3-H3. The level of synchrony between dyads will vary depending on the type of play. Free play, a child-led, spontaneous style of play may show higher variability in coordination while structured play might elicit more consistent, task-dependent alignment between the two (Pellegrini & Smith, 1998; Vandell, 2000).

These research questions and hypotheses will allow us to further address how reliably such coordination can be captured using modern computational tools and how nonverbal movement synchrony unfolds in naturalistic parent-child interactions. By evaluating the NICE Toolbox as a measurement framework to examine synchrony across free and structured play, this study has the potential to advance ecologically valid methods for studying parent-child interactions. This study can have further implications for developmental and clinical science through the development of tools that can be crucial in identifying early interactional difficulties in clinical or educational settings.

3. Methods

3.1 Participants and Procedure

3.1.1 Participants

Data collection for this study took place over the past year and included 16 parent-child dyads: 4 mother-son, 3 father-son, 5 mother-daughter, and 4 father-daughter dyads. The children were between 4 and 10 years old, and the parents were between 34 and 50 years old. Table 1 presents key information about the participants.

Table 1

Participant Demographics and Summary Statistics (M, SD, Min, Max)

Parent Sex	Child Sex	Parent Age	Child Age
f	m	43	5
m	m	39	5
f	f	38	5
f	m	48	6
m	m	50	6
m	f	39	4
f	f	44	4
f	m	37	5

m	f	44	4
f	m	35	6
m	m	36	6
f	f	38	10
f	f	34	6
m	f	38	6
f	f	36	5
m	f	47	8
	M	40,375	5,6875
	SD	4,95143077	1,537042615
	Min	34	4
	Max	50	10

3.1.2 Recruitment

Participants were all recruited from the Ludwig-Maximilians-Universität (LMU) outpatient clinic for child and adolescent psychotherapy in Munich, Germany. This allowed us to access parent-child dyads going through psychological treatment. Paired with video-feedback interventions, parents were asked if they were willing to participate in the study. It was explicitly clarified to the participants that their participation in the study would not affect their ongoing psychotherapy and that the data would be processed and examined independently from the diagnostic process. Written consent was obtained, and appointments were independently scheduled for the study, separately from the standard psychological assessments. The participants who chose to participate were also informed about their right to withdraw at any time, without consequences *(See Appendix I for the Consent Form)*.

3.1.3 Set up and Video Recording Process

Dyads were seated opposite each other, slightly turned towards the camera. Interactions were recorded using an Osmo Action 3 camera positioned in front of the participants. The video recording was set to 50 frames per second, enabling the NICE Toolbox to process movement at the same temporal resolution resulting in 50 data points per second for each body joint. To ensure accurate pose estimation, participants were seated at a table opposite of each other, allowing the software to detect their positions and movement in a standardized and unobstructed manner.

3.1.4 Procedure

The study involved a video paradigm conducted in a dedicated video room at the outpatient clinic. Each dyad completed two play conditions:

1. **Structured Play Condition:** Participants were asked to play the board game "*Save the Penguin"*, requiring cooperative turn-taking to remove pieces of 'ice' without letting the penguin fall.
2. **Free Play Condition:** Participants were given a box of toy animals and were allowed to play without rules or instructions.

Each condition lasted 5 minutes. The instructor left the room during play and knocked to indicate ‘begin play’ and ‘stop play’ at the end of the 5 minutes. In some cases, when play extended 5 minutes, it was left uninterrupted to maintain a naturalistic interaction and all video material was used for following data analysis. Participants were reminded that they could leave, pause or terminate the game at any time.

3.2 Implementation and Adaptation of the NICE Toolbox

Once the experiment was completed, all videos were compiled and carefully transferred on a computer labelled p1g1; p1g2 (Participant 1, Game 1 or 2). This allowed for a clear naming system for all videos which were then ready for processing on the NICE Toolbox. The Toolbox, a preconfigured Max-Planck Institute (Tübingen, Germany) supported framework was provided to us as a preinstalled system in the same computer where all the videos were stored. This ensured a standardized, reproducible processing environment with minimized variability related to system transferring or system dependencies.

Once the data was prepared, the first step was to load the calibration file on Visual Studio Code (Microsoft), generated from the camera calibrations performed in the *Set up and Video Recording Process*, and input the files which were to be processed. Next, the NICE Toolbox was loaded by clicking ‘open folder’ on the Calibration document. Once the Toolbox was open it was important to select the required detector for this study, ‘body_joints’. This component directly allowed us to capture whole-body movement dynamics relevant for assessing nonverbal movement synchrony while avoiding unnecessary complexity from other detectors. Additionally, we also had to input the amount of frames in each video by multiplying the total seconds times 50 (eg., if the video was 6 min long, 360s x 50 = 18000). The software then applied body pose estimation using

ViTPose, a deep learning model optimized for high-precision full body joint detection (e.g., shoulders, elbows, hips, wrists, and ankles) (Xu et al., 2022). The video was then processed by the software frame by frame at 50 frames per second, resulting in a time series of body joint (x, y) coordinates for each detected body joint across the entire interaction. In turn, this produced nearly 1,020,000 data points for each play condition, reflecting continuous movement trajectories over time. The final output from the NICE Toolbox consisted of structured CSV files containing all body joint x, y coordinates along with their confidence scores which serve as raw input for subsequent movement synchrony and windowed cross-correlation analyses.

A key novelty of the present study is the methodological use, and evaluation of *confidence scores*. These scores, provided by the NICE Toolbox were introduced as a part of the most recent update of the software which has not yet been extensively examined or validated in dyadic research. These scores play a crucial role in addressing *RQ 1*, which aims to examine whether the NICE Toolbox is a reliable and valid tool to capture nonverbal movement patterns. *Confidence scores* present an explicit, frame-by-frame estimate of reliability of the detected joint positions, allowing us to not purely rely on an automated algorithm but also actively assess the validity of the extracted raw data. Especially concerning naturalistic interactions, it is important to have such measures which aid the data-cleaning and validation process advancing the methodological approach of movement synchrony research. This can prove to be an important contribution to the validity of the NICE Toolbox in developmental and clinical contexts.

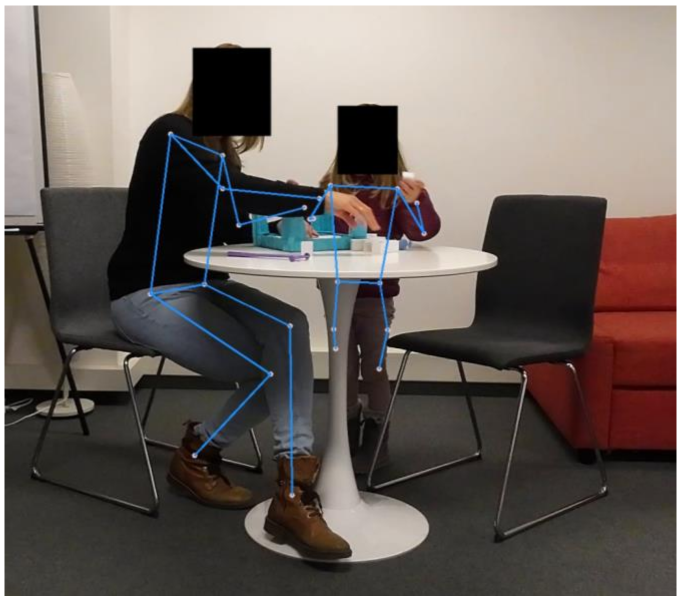
Alongside raw coordinate data, the NICE Toolbox also outputs a *confidence score* ranging from 0.0 to 1.0 for each joint estimate in every frame. In a few exceptions, values can exceed this range due to numerical precision limits or post-processing artifacts (such instances were treated conservatively during data cleaning). The confidence score is computed internally by the pose estimation algorithm ViTPose, which regresses a heatmap for each joint representing the likelihood for the joint being at every pixel location (Xu et al., 2022). The joint position is then aligned to the peak of the heatmap which is the location with the highest likelihood and the corresponding value is reported as the confidence score. During the kinematic calculation step performed by the NICE Toolbox done by measuring movement access consecutive frames, the lower confidence score of the two frames is retained to ensure a conservative estimate. Joint estimates which fall below a predefined threshold, as discussed amongst researchers, can be identified as unreliable and excluded during pre-processing. The final output from the NICE Toolbox consists of structured CSV files containing all body joint x, y coordinates which serve as raw input for subsequent movement synchrony and windowed cross-correlation analyses. A detailed, step-by-step instructions manual on how to run the NICE Toolbox is given in *Appendix II.*

3.3 Pretest Data Processing

With regards to *Hypothesis 1,* prior to preprocessing the raw data, a pretest was conducted to evaluate the quality and reliability of the movement data generated by the NICE Toolbox. The primary goal of this pretest was to perform a *primary behavioral observation*. This was done by reviewing video and frame-by-frame picture visualizations of the assessed body joint movements in multiple processed videos. These videos were examined to determine whether the software was able to detect body joint movements accurately across all frames (*See Appendix III for Primary Behavioral Observation Notes).* While most joint positions were estimated correctly, there were a few situations when the software wasn't able to accurately pinpoint the movement of a body part. For example, the software would predict the position of a leg or an arm incorrectly relative to its actual position in the video. Despite these errors being relatively rare, they were evident and lasting long enough to warrant control. As incorrect movement could then affect subsequent movement synchrony analyses.

Figure 5

Example Frame of a Body Pose Estimation Error Identified During Pretest Validation, Highlighting a Mismatch Between The Detected Joint Position and True Body Posture



***Note*:** The confidence scores of the knee joint and ankle joint were 0.12 and 0.08 respectively.

In order to address these concerns and discrepancies, we investigated the confidence scores provided by the NICE Toolbox for each estimated joint in every frame and then corresponded them to the video visualizations. Since these scores reflect the algorithm's level of certainty about the accuracy for joint detection, we were able to spot a consistent pattern by cross referencing these data points with the identified visible misplacements. The incorrectly detected joint positions in the videos or pictures were associated with low confidence scores, typically below **0.4**. This suggested that controlling the confidence scores could serve as an objective measure for filtering out unreliable data points. Therefore, based on further primary behavioral observations, we defined three potential thresholds for data exclusion/inclusion to systematically control for software errors while also retaining as much valid data as possible.

1. **0.0 Threshold** - no data points removed, effectively using all joint estimates.
2. **0.2 Threshold** - all data points with confidence scores below 0.2 were removed. This allowed us to eliminate only the most obviously incorrect points while retaining the majority of the valid data.
3. **0.4 Threshold** - all data points with confidence scores below 0.4 were removed, representing a more conservative approach of data inclusion which prioritized data quality but risked discarding more potentially valid information.

These three thresholds were tested on the pretest videos using RStudio to determine the most appropriate balance between data integrity and completeness. The evaluation showed that the 0.2 threshold provided the most optimal compromise as it seemed to remove all the extremely inaccurate points while preserving the majority of usable data. Consequently, for all the following analyses, we excluded all body joint coordinates data points with confidence scores below 0.2. A more detailed description of this pretest procedure, including frame-by-frame visualizations, confidence score comparisons are provided in *Appendix III and IV.*

3.4 Preprocessing Raw Data

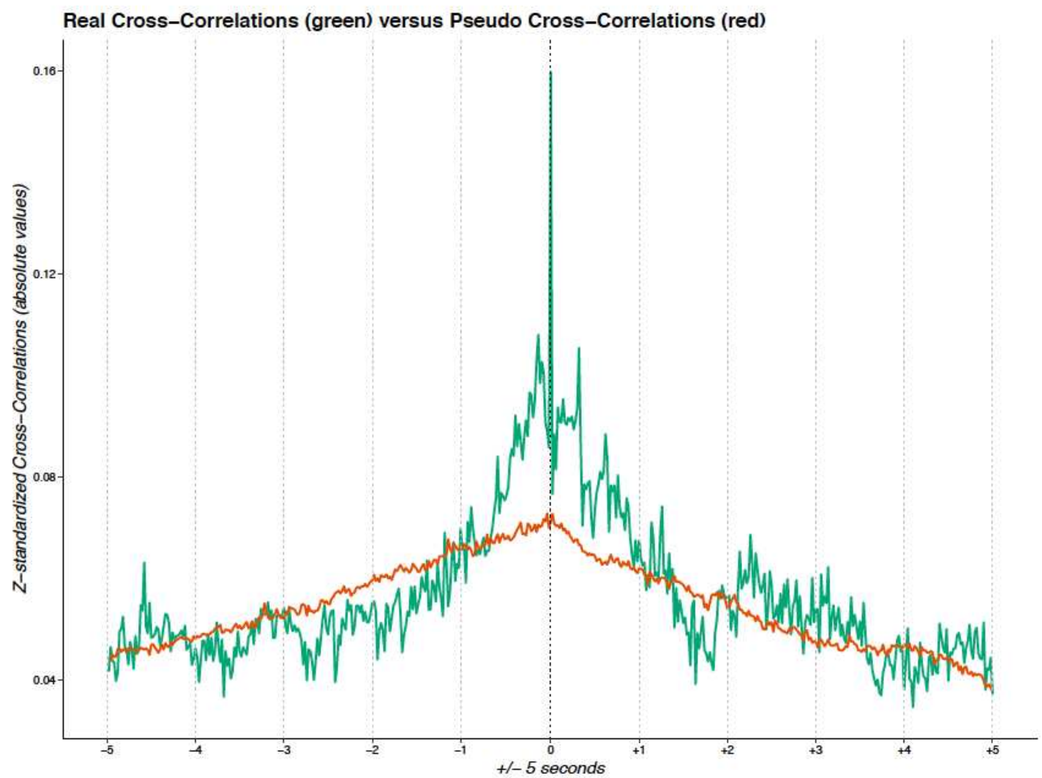
Once the optimal threshold for confidence scores was affirmed in the pretest phase, all the remaining data points were refined by excluding (N/A) joint estimates with all confidence scores below 0.2. The remaining high-confidence data points were then combined into a large data set for each dyad and each play condition (p1g1, p1g2). All data preprocessing, including exclusion procedures, was performed in R (Version 4.2.1), where all subsequent statistical analyses were also conducted.

Considering *Research Question 2*, movement synchrony analyses were performed using the Surrogate Synchrony (SUSY) R package developed by Wolfgang Tschacher, 2019. The Surrogate Synchrony (SUSY) analysis package conceptualizes movement synchrony as the degree of temporal coordination between two simultaneously occurring processes, using windowed cross-correlations. The current study uses this package by representing bivariate time series derived from the movement data of the parent and the child.

Effectively, cross-correlations for each dyad were computed through a fixed temporal segment of each time series. We divided each participant's time series into overlapping segments of 10 seconds. Then, we established a predefined range of *Temporal Lags* (± 5 seconds), specified by the *Maxlag Parameter* that allowed us to calculate correlations within each time segment (Tschacher, 2019). Using *Fischer's Z* Transformation, correlation coefficients were then transformed and regardless of direction, absolute values were used to quantify the overall strength of coordination (Tschacher, 2019). At the segment level, all *Mean Z-Values* were first computed and then aggregated across all segments, which resulted in an **overall synchrony index** *(Mean Z-Value)* (Tschacher, 2019). This overall synchrony index was then applied for each dyad and condition. This allowed the SUSY computation to have flexibility in sampling frequency and segment duration while preserving interpretability (Tschacher, 2019). Below is an example of time-lagged windowed cross-correlations from -5 to +5 seconds for an exemplary dyad. In this figure, we can see the true differences between pseudosynchrony and real synchrony in a dyad. While being mostly similar, the peaks of real synchrony are evidently higher than pseudosynchrony with highest cross-correlations close to time lag 0, representing simultaneous movement.

Figure 5

An Example of a Windowed Cross-Correlation for One Dyad in the Free Play Situation (p6g2) Produced by the SUSY Framework



Note: The red line represents pseudosynchrony whereas the green line represents pseudosynchrony. The x-axis shows the time-lag whereas the y-axis shows the Z-standardized cross-correlations, which are the absolute values transformed using Fischer’s Z Transformation.

Regarding *Research Question 2*, determining whether observed synchrony exceeded synchrony expected by chance, the SUSY framework applied a surrogate data approach (Tschacher, 2019). Based on segment shuffling, this framework randomly reordered segments of one time series relative to the other (Tschacher, 2019). This generated multiple surrogate time series while preserving the original temporal structure of previous segments (Tschacher, 2019). The synchrony computations are then repeated on each surrogate, resulting in a distribution of following surrogate *Mean Z-Values* (Tschacher, 2019). This resulted in an *Effect Size (ES) calculation*, which quantified the extent to which observed synchrony can or cannot exceed pseudosynchrony (Tschacher, 2019).

Therefore, SUSY provides us with two synchrony measures for each bivariate time series: the *Mean Z-Value*, and the *Effect Size (ES)* (Tschacher, 2019). The *Mean Z-Value*, represents the magnitude, or degree of synchrony, whereas, the *Effect Size (ES)*, represents the level of synchrony relative to chance (Tschacher, 2019). The present study uses this framework to compute synchrony across predefined pairs of time series. Visual outputs of such time series plots and cross-correlation profiles can also be generated to visualize the preprocessed data.

Detailed information on this algorithm coded by David Leander Tschacher under the supervision of Wolfgang Tschacher along with instructions regarding its use can be found in *Appendix V & VI*.

3.5 Statistical Analyses

All statistical analyses were conducted on RStudio (Version 4.2.1). As mentioned before, the dataset was cleaned ensuring all data points with confidence scores below 0.2 were removed and set to N/A. This ensured only reliable movement estimates which were withheld for further statistical analyses.

Firstly, using the *describe()* function from the *psych* package, all descriptive statistics were computed for all variables of interest. This allowed us to examine central tendency, dispersion and distributional characteristics such as means, standard deviations, ranges, skewness and kurtosis. This provided us with an initial overview of synchrony measures across conditions.

3.5.1 RQ 2 - Analysis of Synchrony (Z) vs. Pseudosynchrony (Z.Pseudo)

Addressing RQ2, all synchrony values derived from the *SUSY (Z)* function were directly compared with their corresponding pseudosynchrony values *(Z.Pseudo)*. Once all variables were deemed continuous and metrically scaled, a within-subject (paired) design was used to compare each observed synchrony value with a pseudosynchrony estimate from the same dyad and condition.

Prior to all inferential testing, the normality of difference scores *(Z - Z.Pseudo)* was assessed using the Shapiro-Wilk test *(shapiro.test())*. When assumptions of normality were met, paired samples t-tests were conducted using the *t.test (..., paired = TRUE)* function to compare mean synchrony scores against mean pseudosynchrony scores.

Furthermore, Wilcoxon signed-rank tests were additionally performed as a non-parametric alternative using *wilcox.test(..., paired = TRUE)*. Lastly, effect sizes were quantified by calculating Cohen's *d* for dependent samples, using *cohen.d()* function from effsize package. This provided us with an estimate of the magnitude of synchrony that goes beyond chance.

3.5.2 RQ 3 - Synchrony Comparison between Free and Structured Play

With regards to RQ 3, the data had to be restructured in a wide format where each dyad's corresponding synchrony score for each play condition was presented in the same row, allowing for a comparison within dyads.

Similar to RQ 2, descriptive statistics were first computed separately for each condition using the *describe()* function. Normality of the differences between both play conditions was assessed using the Shapiro-Wilk test *(shapiro.test())*. A paired sample *t.test (..., paired = TRUE)* was conducted following that to compare synchrony levels across play contexts. Parallelly, Wilcoxon signed-rank *wilcox.test(..., paired = TRUE)* tests were conducted as a non-parametric robustness check. Followed by Cohen's *d* for dependent samples to quantify the differences between both conditions.

All data was then visualized using a range of graphical methods through the ggplot2 function. These visualizations were used to illustrate the differences between synchrony and pseudosynchrony, as well as between play conditions, supporting the result interpretation of this study.

4. Results

4.1 Descriptive Statistics

Table 1

Descriptive Statistics for the Full Sample, Structured Play Condition and Free Play Condition Comparing Real Synchrony and Pseudosynchrony

Sample	Synchrony Type	N	Mean	Median	SD	IQR	Min	Max	Skewness	Kurtosis	Normality Flag
Full sample	Real synchrony	32	0.052	0.051	0.006	0.005	0.043	0.071	1.090	1.109	p < .05 (Non-normal)
	Pseudosyn-chrony	32	0.051	0.050	0.007	0.007	0.037	0.067	0.652	0.429	p > .05 (Normal)
Structured play	Real synchrony	16	0.051	0.051	0.006	0.005	0.043	0.067	0.941	1.236	p > .05 (Normal)
	Pseudosyn-chrony	16	0.049	0.048	0.007	0.006	0.037	0.066	0.647	0.885	p > .05 (Normal)
Free play	Real synchrony	16	0.053	0.052	0.007	0.008	0.045	0.071	0.992	0.256	p > .05 (Normal)
	Pseudosyn-chrony	16	0.052	0.051	0.006	0.007	0.044	0.067	0.679	-0.392	p > .05 (Normal)

***Note*:** Represented columns: N = sample size; Mean = mean synchrony or pseudosynchrony; SD = standard deviation; Median = median synchrony or pseudosynchrony; IQR = interquartile range; Min = minimum synchrony or pseudosynchrony value; Max = maximum synchrony value; Skewness = tail of distribution; Kurtosis = tail weight of distribution; Normality Flag = representing whether the distribution is normal or not.

All descriptive statistics were computed through RStudio to provide us with an overview of real synchrony *(Z)* vs pseudosynchrony *(Z.Pseudo)* across the full sample and within each play condition. Across the full sample *(N = 32)*, the mean real synchrony resulted in a value of *Z* =

0.052 (SD = 0.006), with a median of *0.051* and values ranging from a minimum of *0.043* and a maximum of *0.071*. On the other hand, pseudosynchrony showed a slightly lower mean *(Z.Pseudo = 0.051; SD = 0.007)* with a median of *0.050* and a slightly wider range with a minimum of *0.037* and a maximum of *0.067*. There was a moderately positive skewness of *1.090* in the real synchrony values and an elevated kurtosis of *1.109*, and normality of the distribution was tested via the Shapiro Wilk test which resulted in values of $p = 0.0131$ representing a deviation from normality ($p<0.05$). In contrast, pseudosynchrony values showed a lower skewness *(0.652)* and kurtosis *(0.429)* and did not deviate from normality with $p = 0.1094$ ($p>0.05$).

When comparing the two play situations, structured and free play, the structured play condition *(N=16)* had synchrony values with a mean of *Z = 0.051 (SD 0.006)* and a range of *0.043 to 0.067*. Pseudosynchrony values were slightly lower *(Z.Pseudo = 0.049, SD = 0.007)* and a range of 0.037 to 0.066. Both real and pseudosynchrony were normally distributed with $p = 0.0702$ and $p = 0.2649$, respectively ($p>0.05$). Both had a moderately positive skewness and kurtosis representing a right-tailed distribution with no substantial deviations from normality.

Comparatively, the free play condition *(N = 16)* showcased synchrony values with a slightly higher mean of *Z = 0.053 (SD = 0.007)* and a larger range of *0.045 to 0.071*. Pseudosynchrony presented with a slightly lower mean of *Z.Pseudo = 0.052 (SD = 0.006)* with a smaller range of *0.044 to 0.067*. Similar to the structured play condition, both variables were normally distributed with $p = 0.1060$ and $p = 0.3320$ ($p>0.05$). Skewness was moderately positive *(0.992)* and kurtosis of *0.679*. The free play condition also represented a right-tailed distribution with no substantial deviations from normality.

Overall, in accordance with the hypotheses for RQ2 and RQ3 the descriptive patterns indicated slightly higher levels of real synchrony compared to pseudosynchrony across conditions, along with a higher mean synchrony observed during free play compared to structured play. Furthermore, this comparatively low level of variability suggests that the overall synchrony values were relatively stable across dyads and play conditions.

4.2 Real Synchrony versus Pseudosynchrony

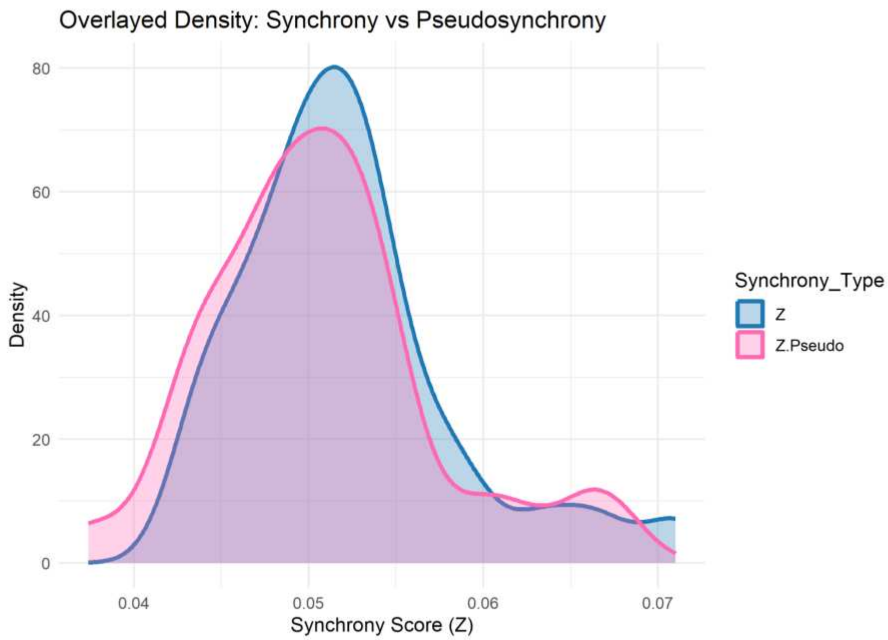
With regards to RQ2, comparing real synchrony and pseudosynchrony amongst the full sample *(N = 32)* was first examined for normality through the Shapiro-Wilk test. The results indicated a slight deviation from normality ($W = 0.89$; $p = 0.03$), indicating that the assumption of normality was violated. Nonetheless, given the continuous and metrically scaled nature of the data and a level of robustness of the paired samples *t*-test, a paired samples t-test was conducted to compare the values of real synchrony *(Z)* vs pseudosynchrony *(Z.Pseudo)*. This analysis revealed a statistically significant difference between the two, $t = 4$ .69, $p < 0.001$, suggesting that values of real synchrony were significantly higher than values of pseudosynchrony. This result aligned with the hypothesis.

Due to the normality violations, an alternative, non-parametric Wilcoxon signed-rank test was also performed and the results were significant ($V = 490$, $p < 0.001$). This helped us confirm the accuracy of the observed effect. Additionally, an effect size estimation using Cohen's d for dependent samples indicated a small effect of $d = 0.24$.

Results are visualized below using the *ggplot* function on RStudio. The visualizations illustrate the distribution and central tendency differences between real synchrony and pseudosynchrony between dyads through a density plot and a box plot.

Figure 6

A Density Plot Representing Density Overlays Between Synchrony and Pseudosynchrony in the Full Sample (N = 32)

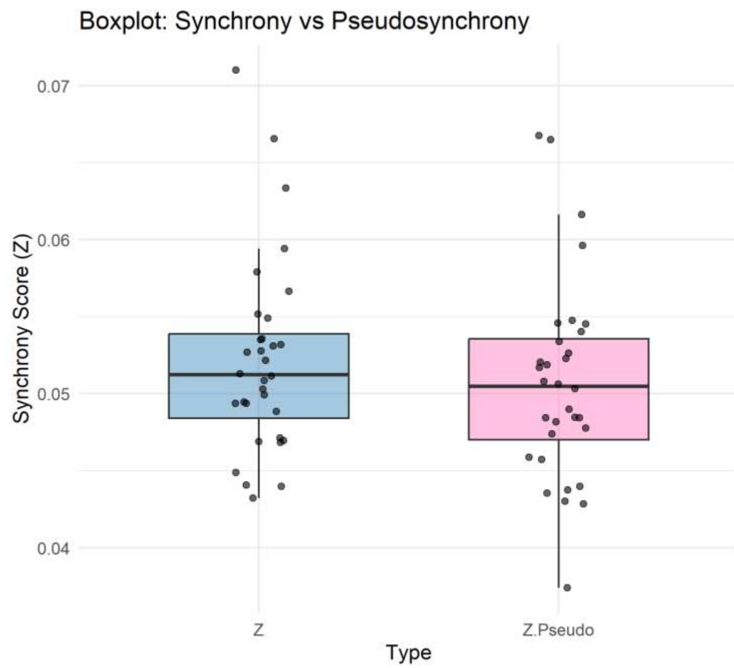


Note**:** The density plot above illustrates the distribution of synchrony vs pseudosynchrony where the x-axis represents the Synchrony Score (Z) whereas the y-axis represents the level of density in the full sample (N = 32). The blue curve represents real synchrony whereas the pink curve represents pseudosynchrony.

The density plot above visualizes the distribution and overlap between real synchrony and pseudosynchrony across all conditions with the full sample. Overall, the plot demonstrates a high level of overlap between the two distributions indicating that synchrony levels were mostly similar. However, as presented in the descriptive statistics, real synchrony showed a slightly higher central tendency *(M = 0.052)* compared to pseudosynchrony *(M = 0.051)*. Additionally, a slight right skew is also evident in both peaks with pseudosynchrony values demonstrating a slightly wider spread.

Figure 7

A Boxplot Illustrating the Overall Distribution of Real Synchrony (Z) vs Pseudosynchrony (Z.Pseudo) Scores in the Full Sample (N = 32) Across Both Play Conditions (Structured and Free)



***Note*:** The boxplot above represents both real synchrony and pseudosynchrony scores across the full sample in both play conditions. The x-axis contains both types of synchrony whereas the y-axis represents the synchrony score (Z). The blue box represents real synchrony whereas the pink box represents pseudosynchrony.

The boxplot comparing real synchrony and pseudosynchrony also provides an accurate visualization of the central tendency and slight variability across the sample. Median synchrony values are slightly higher for real synchrony (Md = 0.051) as compared to M = 0.050. Real synchrony also presents a comparatively narrow central distribution with several higher value observations which contribute an overall positive skew. Pseudosynchrony presents with a slightly broader spread with lower minimum values (*Min* = 0.037), all of which demonstrating the narrowly elevated real synchrony values compared to pseudosynchrony values.

Overall, the descriptive statistics and visualizations indicate that observed real synchrony was significantly higher than pseudosynchrony, aligning with the hypothesis for RQ2. Nonetheless, the differences were still relatively small allowing for considerable overlap. The paired samples *t*-test and the Wilcoxon signed-rank test, however, supported our claim of a reliable synchrony effect over pseudosynchrony. A small effect size also suggests that the effect of synchrony over pseudosynchrony is small yet significant in naturalistic parent-child interactions.

4.3 Structured Play versus Free Play

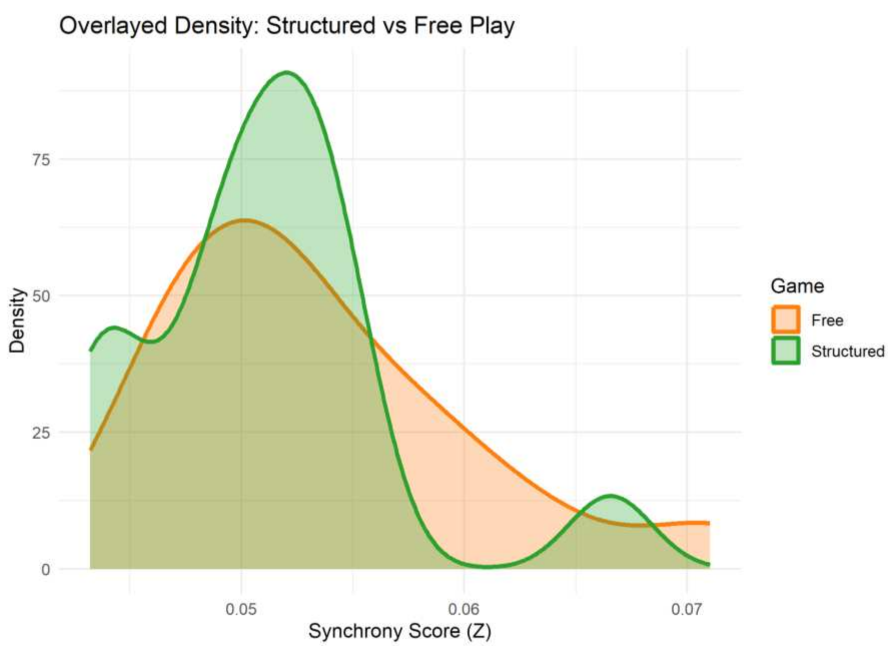
While comparing synchrony scores between the two play conditions, structured and play, inferential tests were performed. Prior to the inferential tests, the normality of the difference was assessed using the Shapiro-Wilk test. The results indicated that the assumption of normality was met ($W = 0.97; p = 0.91$), supporting the use of parametric analyses such as the paired samples t-test. Therefore, a paired samples *t*-test was therefore conducted to compare synchrony scores between the two play conditions. The analysis presented no statistically significant difference between the two conditions, $t = -1.44, p = 0.17$ ($p > 0.05$), indicating that the synchrony levels were not reliably different between the compared play conditions.

To account for this, a non-parametric Wilcoxon signed-rank test was also performed and consistent with the parametric findings the results were also non-significant with $V = 44, p = 0.23$ ($p > 0.05$). An effect size measure was also conducted with Cohen's *d f*or dependent samples which presented a small to moderately negative effect with $d = -0.37$ indicating a slight tendency towards lower levels of synchrony in the structured condition, however, this difference was not statistically significant.

Similar to RQ2, visualizations comparing structured and free play conditions were developed using the *ggplot* function on RStudio. The data was visualized using a density plot and a boxplot to illustrate the distribution and overlap of the synchrony values across the two conditions.

Figure 8

A Density Plot Representing Density Overlays of Real Synchrony (Z) Values Between Structured (N = 16) and Free (N = 16) Play Conditions

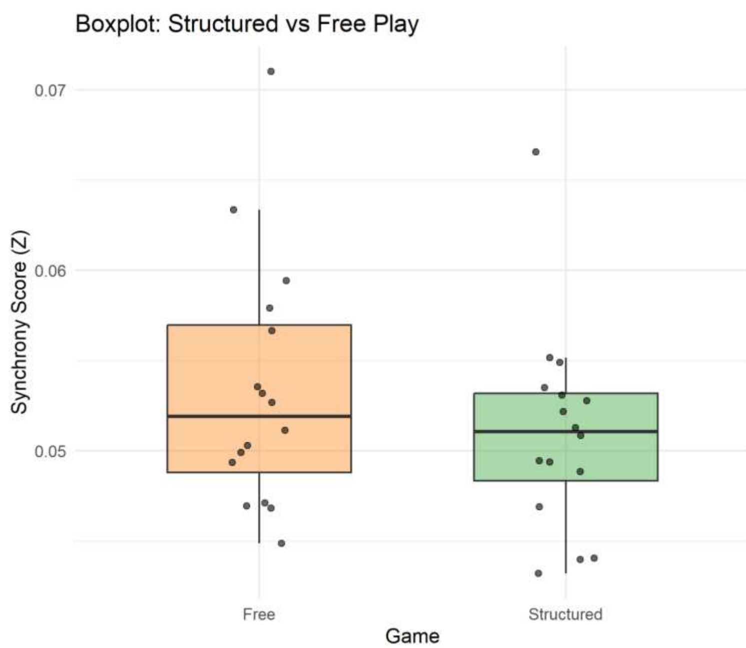


Note**:** The density plot above illustrates the distribution of real synchrony (Z) values between structured (N = 16) and free (N = 16) play conditions. The x-axis represents the Synchrony Score (Z) whereas the y-axis represents the level of density. The green curve represents the structured play condition whereas the orange curve represents the free play condition.

The density plot above compares real synchrony across both play conditions and indicates a marginal rightward shift for free play as indicated by the descriptive statistics (*M* = 0.053) as compared to structured play (*M* = 0.051). The free play condition also displays a slightly wider spread compared to structured play. Overall, both curves largely overlap while the free play condition showed higher synchrony levels.

Figure 9

A boxplot illustrating the overall distribution of real synchrony (Z) scores in the two play conditions, structured and free.



***Note*:** The boxplot above represents real synchrony (Z) scores in both the Structured and Free play conditions. The x-axis (‘Game’) represents the play condition (Structured and Free) whereas the y-axis represents the Synchrony Score (Z). The orange box represents the Free play condition whereas the green box represents the Structured play condition.

The boxplot above comparing real synchrony across structured and free play conditions illustrated a slightly higher median in the free play (Md = 0.052) condition as compared to structured play (Md = 0.051). Free play demonstrated slightly greater variability and a higher maximum value (0.071) compared to structured play (0.067) both of which contribute to a positive skew in both conditions. Overall, the boxplot visually illustrated that synchrony levels were comparable across both conditions with free play showing a slight tendency towards higher variability and higher synchrony values.

Overall, across both play conditions the pre-processed data suggested that synchrony levels were slightly higher for free play compared to structured play. However, this was not supported by inferential analyses and did not prove to be statistically significant through the paired samples *t*-test and the Wilcoxon signed-rank test. Therefore, the hypothesis for RQ3 could not be backed up by statistical measures. These results could suggest the need for moderating factors beyond play structure which would be an important point for the forthcoming discussion. The implications for developmental interactions dynamics and other methodological considerations and limitations will also be discussed further. All the R-Scripts created for descriptive analyses and inferential analyses are present in *Appendix VII.*

5. Discussion

5.1 Overview of the Current Study

The current study explores interpersonal movement synchrony in parent-child dyads through the use of a novel software, the NICE Toolbox. The primary question this research addressed was evaluating whether the NICE Toolbox is a suitable, reliable and valid method to assess nonverbal movement synchrony in naturalistic parent-child interactions. The NICE Toolbox was implemented in this study because earlier methods to analyse movement synchrony such as MEA were riddled with several methodological limitations *(see Section 2.5*). Therefore, the NICE Toolbox provided us with a new, advanced technique to observe movement synchrony using advanced algorithms like ViTPose, employing body pose estimation techniques, capturing fine-grained kinematic information out of video data. Hence, the present study sought to examine whether this state-of-the-art framework could provide a robust alternative to study movement synchrony in developmental contexts.

Parent-child dyads were observed during two interaction paradigms, structured and free play. In the structured play context, participants were asked to play the *Save the Penguin* board game whereas in free play, participants were asked to play freely with the toys provided to them. Synchrony analyses were operationalized through windowed cross-correlation analyses which generated a mean Z-Score for each dyad in each play condition. Observed coordination (Real Synchrony) was then compared to synchrony expected by chance (Pseudosynchrony), computed via a segment-shuffling procedure *(see Section 3.4)* within the Surrogate Synchrony framework. This approach provided a direct comparison between real temporal coordination and synchrony that could emerge randomly from the structure of the data. Similarly, the two play contexts, structured play and free play were also compared to assess whether interactional structure can influence the presence of synchrony in naturalistic interaction contexts.

Therefore, three research questions guided this investigation. RQ1, examining the reliability, validity and practical usability of the NICE Toolbox. RQ2, investigating whether observed real synchrony significantly exceeded by chance pseudosynchrony. RQ 3, exploring whether synchrony levels differed significantly between the two play contexts, structured play and free play.

Existing literature allowed us to develop corresponding hypotheses for RQ2 and RQ3 which provided a strong framework for the empirical analyses. For RQ2, we hypothesized that observed synchrony between parent and child would significantly exceed pseudosynchrony levels. Consistent with prior research, this demonstrates that interpersonal coordination typically surpasses chance-based alignment. For RQ3, we hypothesized that free play would yield greater variability in coordination while structured play might elicit more consistent task-dependent alignment between the two individuals.

The following *Discussion* section will aim to address all three research questions sequentially and consider the broader theoretical implications, methodological limitations and future directions for movement synchrony research in developmental and clinical settings.

5.2 Validating the NICE Toolbox

In sum, the NICE Toolbox has proven to be a user-friendly, reliable and scalable alternative for researchers who wish to study nonverbal movement synchrony - even for young researchers with limited prior experience with computer vision or movement analysis softwares. Learning to operate the toolbox was a smooth process aided by a step-by-step workflow provided by the developers allowing us to adapt and quickly process videos without extensive training (*See Appendix II)*. Furthermore, the developers of the toolbox at MPI Tübingen were always reachable and responsive as they provided practical guidance making it easy to solve any hiccups or troubleshoot forthcoming issues with the software. Overall, our personal experience with the toolbox understates a high level suitability and reliability for research groups with varying levels of technical experience.

The NICE Toolbox integrates multiple computer vision algorithms to track and analyse human movement and behaviours. With regards to the present study, the NICE Toolbox used the algorithm, ViTPose, which provided frame-by-frame x and y coordinates for body joints at 50 frames per second (Xu et al., 2022). These data can be further processed to calculate kinematic variables such as displacement and velocity which form the foundation for movement synchrony analyses (Xu et al., 2022). In our case, the setup came as a pre-installed software on a MPI Tübingen computer which made it readily usable. Once processed, the videos were labelled eg., p1g1, p1g2 to reflect structured (g1) and free (g2) play conditions. The output is automatically stored in CSV files ready for a direct import into R for further analyses.

The introduction and evaluation of confidence scores were a key novelty of the newest version of the NICE Toolbox. Confidence scores were included along with the x and y coordinates of body joints. These scores provided a ‘reliability estimate’ for each joint position, ranging from 0.0 (low reliability) to 1.0 (high reliability), with a few exceptions going below 0.0 or above 1.0 due to numerical precision or artifacts. These scores allowed us to be systematic and methodologically rigorous when assessing the raw data. During our primary behavioral observation tests, we evaluated three thresholds: 0.0 (no data removed), 0.2 (data with confidence scores below 0.2 were removed), and 0.4 (data with confidence scores below 0.2 were removed). For all prospective analyses 0.2 threshold was selected for all subsequent analyses because it represented an appropriate balance between sensitivity and robustness. The 0.0 threshold risked the inclusion of noisy data points whereas, the 0.4 was more conservative, removing too many data points. Hence, the 0.2 threshold provided a theoretically and statistically defensible compromise while maintaining a high methodological standard. Full results for all threshold analyses, descriptive and inferential are reported in *Appendix III & IV*. This addition significantly enhanced the methodological rigor of the analysis, ensuring that all unreliable data was removed before advancing to the inferential analyses. We urge researchers to explore their own thresholds and conduct threshold evaluations based on their sample and data size.

Despite the aforementioned strengths of the toolbox, some limitations were also noted. When generating video visualizations alongside frame-by-frame photo data, the downloaded files were very large, going up to 600 GB for a single 5-minute video, making long-term storage and processing impractical as we had to constantly switch between hard-drives and storage components. Processing times were also considerably long, up to 4 hours for a 5 minute video even when focusing on only one variable with visualizations. Without video visualizations, however, this processing time was cut down to 2 hours for a 5 minute video. However, in many discussions with the developers, they have indicated that improving the processing speed and memory efficiency is one of their primary goals for future updates.

Altogether, the NICE Toolbox offers an immense potential for developmental and clinical psychotherapy research. It is an intuitive interface that functions comprehensively and the addition of confidence score provides a strong alternative to traditional movement research such as Motion Energy Analysis. Moreover, with promising improvements in processing efficiency and their open-science nature, the NICE Toolbox is placed strongly to compete with other body pose estimation tools such as OpenPose, surpassing new boundaries for investigating nonverbal synchrony in naturalistic settings.

5.3 Real Synchrony versus Pseudosynchrony

The second research question of this study asked, “How does nonverbal movement synchrony manifest as temporal coordination during naturalistic parent–child interactions (free play vs. structured play), and does observed synchrony significantly exceed pseudosynchrony (i.e., synchrony expected by chance)?” Backed up by previous literature, we hypothesized that both individuals will display movement coordination that exceeds chance, or pseudosynchrony levels (e.g., Ramseyer & Tschacher, 2011; Delaherche et al., 2012). In essence, real synchrony will be significantly higher than pseudosynchrony.

Synchrony scores were computed using windowed cross-correlations, through a statistical procedure developed by Wolfgang Tschacher (2019), known as Surrogate Synchrony (SUSY). This approach divides each participant’s movement time series into overlapping consecutive 10-second segments. By using 10 second segments, this procedure keeps the statistical properties intact, allowing us to shuffle the alignment between parent and child. Within each segment, the cross-correlations between the parent’s and child’s movement signals are calculated at multiple temporal lags (±5 seconds). This allowed us to capture how movement signals are aligned over time, including any delays in response between the dyad. On the other hand, pseudosynchrony represents the level of synchrony expected purely by chance, i.e., the structure of the data. To calculate pseudosynchrony using the SUSY approach, we divided each dyad’s movement time series into fixed temporal segments of 10 seconds. The order of these segments is then shuffled to create a surrogate, ‘proxy’ time series. This ensures that any results derived from the surrogate time series represent chance, or pseudo-coordination rather than true interpersonal synchrony. These surrogates are computed as cross-correlations for each segment and aggregated across all groupings to generate pseudosynchrony scores against which observed synchrony can be compared. Sequentially, to quantify synchrony, the correlation coefficients were transformed using *Fisher’s Z transformation*, so that both positive and negative coupling contribute to a synchrony score. These segmented Z-values are then averaged to create a **Mean Z-Value** for each dyad in each play condition. Real synchrony values were represented through Z scores whereas pseudosynchrony values were represented through Z.Pseudo. All the dyads synchrony and pseudosynchrony scores were aggregated to provide us with a comparison between the two groups.

Along with segment shuffling, there are a few other methods used to distinguish genuine interpersonal coordination from chance-level alignment (Ramseyer & Tschacher, 2011). While in segment shuffling, temporal segments of one partner’s time series are randomly reordered to create a proxy, in dyad shuffling, time series form one participant is paired with data from an unrelated partner (Ramseyer & Tschacher, 2011). This maintains the natural temporal structure of each individual's behaviour but removes the interactive coupling between the original dyad (Ramseyer & Tschacher, 2011). Another method involves phase randomization (Paxton & Dale 2017). Here, the temporal structure of a signal is mathematically altered via Fourier-based techniques, while preserving the overall statistical properties such as mean and variance (Paxton & Dalem 2017). Together, these procedures all help strengthen the methodological rigor of synchrony analyses by providing strong baselines against real-time coordination. Compared to other methods, segment shuffling retains the temporal granularity needed for windowed cross-correlation analyses (Ramseyer & Tschacher, 2011). This method proves to be an interpretable way to extract pseudosynchrony estimates while preserving overall dynamics of the dyad (Ramseyer & Tschacher, 2011). By randomly reordering segments of one participant's time series, this method only disrupted the moment-to-moment alignment between patterns without altering the variability or structure of their movements (Ramseyer & Tschacher, 2011). This provided us with a direct comparison between real synchrony and pseudosynchrony.

Once the data was analysed the results indicated that real synchrony was significantly higher than pseudosynchrony. Both the paired samples *t*-test *($t = 4.69$, $p < .001$)* and the Wilcoxon signed-rank test *($V = 490$, $p < .001$)* confirmed that this difference was statistically significant. Although the effect size was small yet moderate *(Cohen's $d = 0.24$)*, the visualizations allowed us to reinforce these results. The density plot for real synchrony illustrated a higher central tendency and narrower distribution with a positive skew and the box plot illustrated a positive skew in real synchrony scores and a broader spread for pseudosynchrony. Overall, the visualizations made it evident that despite there being considerable overlap between the two groups, real parent-child synchrony exceeds synchrony that is due to chance.

Our findings support Hypothesis 2 which predicted that dyads would present a level of coordination that is significantly above chance levels (Ramseyer & Tschacher, 2011; Delaherche et al., 2012). The results support this hypothesis and suggest that even in short (5-7 min), small sample (N = 32), naturalistic interactions, parents and children coordinate with a measurable amount of movement. This indicates that the degree of temporal coupling is a core, foundational aspect of interpersonal behaviour. This is backed up by the segment-shuffling approach which provides a high standard of methodological rigor which future researchers can apply to distinguish genuine dyadic coordination from random or coincidental movement patterns. As a fundamental aspect of developmental psychotherapy research, this allows us to differentiate movement patterns that carry meaningful implications for understanding interaction quality.

One limitation of the results was that the effect size was small, possibly due to a small sample size. However, the consistent significance across both parametric (paired samples *t*-test) and non-parametric (Wilcoxon signed-rank test) tests proves that synchronized movement is a reliable and reproducible phenomenon in naturalistic play contexts. This underlines the importance of applying robust statistical techniques such as windowed cross-correlations and surrogate 'proxy' data comparisons when studying dyadic interactions. Additionally, pose estimation softwares like the NICE Toolbox allow us to capture and quantify fine-grained movement patterns, aiding our study of true dyadic interactions for future research.

In conclusion, our results demonstrate that parent-child dyads display a quantifiable, measurable amount of movement synchrony even during short naturalistic interactions. analysing synchrony measurement against surrogate pseudosynchrony data via segment shuffling provides strong evidence that coordination between parent and child is a core feature of their interaction. These results validate the methodological approach of this study and provide strong a foundation for future research into how synchrony may vary across developmental stages and interaction contexts, reinstating the importance of precise, validated tools like the NICE Toolbox for studying subtle, fine-grained interpersonal dynamics.

5.4 Structured Play versus Free Play

The third research question of this study asked, "Does movement synchrony differ between free play and structured play conditions?" We hypothesized that synchrony levels would vary depending on the type of play. Free play, a child-led, spontaneous play style would elicit greater variability in coordination and potentially higher synchrony peaks as opposed to structured play, as it is a rule-based, task-oriented play style, which can elicit more consistent, goal-directed alignment between parent and child (Pellegrini & Smith, 1998; Vandell, 2000). Once the data was analysed and the Z scores of both groups were compared, we found that our hypothesis could not be statistically backed up. Despite an evident difference underlined by the descriptives, where the means of free play had higher synchrony levels (M = 0.053) compared to structured play (M = 0.051), the inferential statistics did not highlight a significant difference. Once the assumption of normality was met, we conducted a paired sample *t*-test *($t = -1.44$, $p = 0.17$ ($p > 0.05$))*. The *t*-test revealed no significant difference in synchrony between the two play conditions. Hence, we conducted a non-parametric alternative, the Wilcoxon signed-rank test *($V = 44$, $p = 0.23$ ($p > 0.05$))*, which reinforced the findings of the *t*-tests. Hence, the hypothesis that synchrony would differ as a function of play was not supported by the inferential data analyses.

Despite this statistical insignificance, the effect size (Cohen's $d = -0.37$) revealed that there was a small-to-moderate negative effect, suggesting a slight trend towards lower synchrony in the structured play condition relative to free play. This trend aligns with the theoretical expectation that free play may foster more dynamic, spontaneous coordination (Pellegrini & Smith, 1998) . Additionally, the higher means demonstrated during the free play condition were represented in a slight rightward shift in the density graph. The box plot further illustrated that the free play condition had greater variability and a higher maximum value (0.071). This suggests that while average synchrony levels were similar, some dyads have achieved high coordination during free play. Perhaps, with a larger sample size this observation could have been more evident. On the other hand, structured play appeared slightly more constrained in its range, which may have been due to the turn-taking, rule-based demands of the task (Vandell, 2000).

Altogether, these results indicate that the degree of movement synchrony as assessed using a body pose estimation algorithm appears relatively stable across both play conditions within this sample. Non-significant inferential results suggest that the conditional structure of the interaction may not be a strong determinant of movement synchrony in naturalistic parent-child interactions. However, descriptive patterns hint at a slightly more variable interaction when a dyad is asked to play freely, consistent with theoretical expectations. Nonetheless, these results provide us with a foundation for further investigation into contextual effects. It is possible that differences between structured and free play would be more pronounced in larger samples, possibly across different developmental stages or within atypical populations where the nature of interactions may vary (Krijnen et al., 2023). While this study may not offer statistical support for the aforementioned hypothesis that synchrony can differ by play style, it suggests that contextual influences can be complex and research requires moderating factors that go beyond play structure alone or require larger sample sizes where differences can be more pronounced.

5.4 Implications

The current investigation answered three important research questions, all of which can play a pivotal role in future developmental research. The first research question validated the usage of the NICE Toolbox. It allowed us to study whether automated, video-based analytic approaches could be used to detect movement synchrony in naturalistic parent-child interactions. The NICE Toolbox, is a software that is in its infancy and yet, has proven to be up to par with the demands of the methodological rigor required for developmental research. The valuable addition of confidence scores strengthens the methodological dimensions of the toolbox. This paired with the use of windowed cross-correlations and the SUSY (Surrogate Synchrony) framework, aids in reliably quantifying interpersonal movement coordination. The ability to operationalize synchrony research through state-of-the-art softwares such as the NICE Toolbox and subsequent time series windowed cross-correlation analyses, contributes to an ever-growing field of developmental psychology. It suggests that movement synchrony isn't only an observational or theoretical construct, but indeed a measurable phenomenon occurring in naturalistic play scenarios.

The second research question compared real synchrony against chance-level coordination (pseudosynchrony). Real synchrony between parent-child dyads was evidently and significantly higher than pseudosynchrony. This result supports the idea that observed coordination in parent-child dyads reflects genuine interpersonal coordination rather than chance-level alignment. This reiterates that the concept of movement synchrony is an emerging property of two interacting systems (Wilcox et al., 2025; Feldmann, 2007). This suggests that dyads are moving dynamically and constantly reciprocating, reacting and realigning their movements to one another (Leclère et al., 2014). Thus, temporal coordination between dyads that goes beyond randomness or chance-level occurrence is empirically supported through these findings (Feldmann, 2007).

The comparison between the two play conditions suggested that free play has slightly higher and more variable synchrony, however, these descriptive results were not backed up by inferential analyses. This finding suggests that across short-term contextual variations in movement synchrony can prove to be somewhat robust. However, the absence of a significant contextual effect can also imply that synchrony may be quite a stable process with slight variations rather than being dependent heavily on task demands. Although, observing significant contextual differences may be subtle in small samples, whereas larger samples may extract larger contextual differences (Serdar et al., 2020). These findings motivate future researchers to explore multiple variables in larger samples to extract contextual differences that may interact and influence the level of synchrony in parent-child dyads in naturalistic interactions (Roche et al., 2025).

Approaching these findings through a developmental psychology lens, it can be implied that when real synchrony exceeds chance levels, it highlights the importance of true embodied coordination in early developmental processes (Dozier et al., 2013). Furthermore, it underscores that movement synchrony can serve as a mechanism through which dyads can mutually attune, learn, share attention and regulate (Milteer et al., 2012). This combined with small but consistent patterns of coordination can play a role in the development of coordinated understanding, trust and co-regulatory capacities (Bowlby, 2012). Measurable movement synchrony can provide opportunities to examine dyadic or individual differences that can reflect relational quality, development and interaction quality (Grinspun et al., 2024). These differences could help researchers understand how dyadic coordination can contribute to long-term developmental trajectories.

The findings of this study can also have important implications for psychotherapy (Ramseyer & Tschacher, 2011). In interventions with parents and children studying dyadic influence, this research demonstrates that synchrony can be objectively measured and can function as a behavioral marker of interactional functioning (Ramseyer & Tschacher, 2011). Reliable differences evident even in short interactions, suggest that synchrony is a sensitive phenomenon strongly influenced by the level of dyadic engagement. In therapy, movement synchrony can prove to be a process and an outcome (Ramseyer & Tschacher, 2011). Future interventions could be aimed at improving parent-child attunement, responsiveness and co-regulation through movement synchrony as a behavioral marker, whereas inference in the level of movement synchrony could suggest interactional pressure, strain or difficulties in regulation. Hence, synchrony assessments paired with observational measures could make therapeutic processes more dynamic and robust (Ramseyer & Tschacher, 2011). For example, movement synchrony can be assessed through structured parent-training tasks or open-ended play therapy where the capacity of dyadic coordination can persist.

This investigation contributes to existing literature positioning nonverbal movement synchrony as a measurable, theoretically and methodologically grounded, and clinically meaningful phenomenon of human interaction. It also provides a foundation for forthcoming research on how synchrony develops and varies across clinical contexts, and whether it can be used as a tool in developmental and therapeutic frameworks.

5.5 Limitations of the Current Study

Despite considerable positive implications of this study, there are several limitations which must be addressed. One glaring limitation of this study is its small sample size (N = 32; 16 dyads). This limited the statistical power to detect subtle differences in synchrony, especially the contextual differences (Cohen, 1992). The ability to detect significant differences between the two play scenarios may have been due to insufficient statistical power, as small samples often risk Type II errors, meaning that small, possibly meaningful effects shown by descriptives may not reach statistical significance (Cohen, 1992).

Secondly, the duration of play could have been relatively short. Five to seven minutes per condition may not fully represent the dynamic nature of ever-evolving interpersonal synchrony (Ramseyer & Tschacher, 2011). Behavioral synchrony is a sensitive process that has shown to fluctuate through many phases of an interaction (Feldmann, 2007). Short bursts of interactions may hinder true interpersonal interaction and only reflect snapshots of coordination rather than cumulative relational patterns. Longer interaction periods or repeated observations across multiple sessions could provide deeper insight into how synchrony unfolds over time (Ramseyer & Tschacher, 2011).

Thirdly, this investigation relied on high-resolution video data and intensive computational processing procedures, such as movement extraction and time series cross-correlation analyses. This meant that we had to deal with extremely large file sizes (up to 600GB) and long processing times (up to 4 hours per video) which limited the feasibility of applying this methodology in larger samples. In conversations with the developers of the NICE Toolbox, they have proposed that this aspect of the software is on the top of their to-do lists. Streamlining procedures and integrating more efficient automated systems would enhance the applicability of this approach in larger, dynamic samples.

Some measurement limitations must also be addressed. Despite the NICE Toolbox and its confidence score thresholding procedures being implemented to ensure data quality, minor tracking errors or slight variability in confidence scores may have influenced the precision of movement estimates. Our exclusion of low-confidence scores refined our dataset, however, automated video-based tracking is susceptible to slight inaccuracies due to lighting conditions, occlusions, or rapid movement (Cao et al., 2019). In our primary behavioral observations we also noticed that the software was more susceptible to inaccuracy when participants wore black as compared to easily distinguishable colours. Moreover, this experimental set up only included one camera. Perhaps, by including three cameras one facing each individual and one facing the dyad could make data processing more accurate and reduce noise (Schmitt et al., 2025).

Finally, despite the real synchrony versus pseudosynchrony being statistically reliable, due to small effect sizes, the results limited practical or clinical significance of the findings (Cohen, 1988). The small magnitude of effects suggests that while synchrony is detectable, its measurable impact within short interactions may be small. Larger samples and more diverse populations may help clarify whether stronger effects emerge under different relational or developmental conditions.

Altogether, these limitations underscore the need for cautious interpretation and highlight the importance of replication, refining the methodology, expanding the sample and diversifying the population to examine true effects in the future research.

5.6 Future Considerations

The aforementioned limitations of the present study create several directions for future research that would strengthen both, methodological rigor and theoretical understanding of nonverbal movement synchrony. First, increasing the sample size should be an absolute priority in subsequent studies. A large sample would enhance statistical power and hence, allow researchers to detect more subtle effects. Increasing statistical sensitivity would also support more advanced analyses. For example, by moderating variables such as age, gender, temperament, relational quality and conducting subgroup comparisons. By increasing the sample size, researchers can refine the procedure further which can help detect interaction patterns which may not have reached significance in the current study.

Furthermore, by examining longer interaction periods or repeated sessions across time, researchers can attempt studying the dynamic nature of synchrony which fluctuates throughout an interaction as dyads constantly reciprocate, react and realign to one another. By observing longer or multiple interactions, researchers can also explore the stability, consistency and temporal evolution of interpersonal movement synchrony over time. Paired with longitudinal designs, this would allow researchers to study synchrony as a behavioral marker of relational quality.

Additionally, optimizing video processing and data storage procedures will be essential for improving efficiency and scalability. This study validated the usage of the NICE Toolbox and suggested that it's a valuable software that extracts movement data, however, the large video file sizes and computational demands can often limit broader application. Hence, improving compression, storage and enhancing processing times of the NICE Toolbox would facilitate the use of synchrony analyses in larger datasets in variable contexts.

Future studies can also explore additional contextual factors that can influence synchrony. Task complexity, emotional valence, stress factors, parental sensitivity or environmental distractions could be such options explored by researchers which can have an effect on coordination patterns in meaningful ways. Studying how these factors interact with interactional processes has the ability to provide more nuanced results of how synchrony develops and evolves across time.

One key consideration would be to integrate behavioral synchrony measures with other modes of complementary physiological or neural data. This would allow for a multi-modal understanding of dyadic coordination that goes beyond singularity. This could be done by combining movement synchrony with heart-rate variability, cortisol sampling, EEG or fNIRS hyperscanning or electrodermal activity. This could highlight how motor coordination aligns with neural and/or physiological co-regulation. Such an approach would strengthen the interpretative validity of the findings and place them along broader systems and position movement synchrony as a true biomarker in detecting relational quality.

Finally, future researchers can consider extending the sample to atypical populations which can represent an important avenue for applied relevance. Developmental distractions can often lead to disruptions in attachment or relational difficulties (Wright et al., 2023). Examining synchrony in these domains could help clarify whether coordination patterns differ meaningfully from typically developing samples. This would advance theoretical understanding and evaluate synchrony as a potential biomarker in interventions for therapeutic change.

Overall, researchers must consider sample size, temporal score, methodological efficiency, contextual dynamics, multi-modal integration and clinical application with regards to future research. These aspects have the potential to deepen our knowledge of interpersonal synchrony as a marker in parent-child interactions.

6. Conclusion

Our study set off to examine nonverbal movement synchrony in parent-child dyads across structured play and free play conditions using a novel automated video-based software, the NICE Toolbox. This investigation presented that real synchrony significantly exceeded pseudsynchrony, validating the notion that parent-child coordination represents genuine coupling rather than by-chance alignment. Statistically reliable findings mean that this study was able to reinforce the concept of synchrony as a meaningful process that provides us a glance into the relational quality of a parent-child dyad.

However, we weren't able to find any statistically significant differences between the two play conditions. While descriptive patterns proposed slightly higher and variable synchrony during free play, our inferential analyses did not confirm these differences. Altogether, these results propose that interpersonal movement synchrony is present in naturalistic interactions and observable using advanced computational time series methods, even in short time-windows.

Methodologically, this study advances the current state-of-the-art by highlighting the potential of automated movement analysis using the NICE Toolbox in combination with windowed cross-correlations and the Surrogate Synchrony framework. However, it is important to recognize that the NICE Toolbox is still in its infancy as a research software. As it continues to evolve and become more precise, efficient and scalable, its capacity to capture interactional dynamics will likely scale larger. Future developments can reduce processing constraints, improve tracking accuracy and enable broader application in research settings.

Research in interpersonal synchrony is an ever-evolving field. As computational methods such as the NICE Toolbox become more and more refined and better integrate interdisciplinary approaches, the observation of embodied coordination can benefit substantially. The continued advancements in developmental psychology opens promising avenues for examining moment-to-moment coordination in interpersonal relationships across the human lifespan.

To conclude, this study is an important contribution to the growing literature in examining interpersonal synchrony as a detectable and meaningful feature of parent-child interaction. While certain contextual differences were not statistically significant, they lay an important foundation for future research. The methodological innovation of this study expands empirical findings for both synchrony research and the technologies that support it. Developing in tandem, they provide accurate insights into the true dynamics of interpersonal human connection.

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8. Appendix

Appendix I: Consent Form

LMU | LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN | KLINISCHE PSYCHOLOGIE DES KINDES- UND JUGENDALTERS & BERATUNGSPSYCHOLOGIE

Studie zur Eltern-Kind-Interaktion in Spielsituationen

Datenschutzrechtliche Aufklärung und Einwilligung
(inkl. Informationen gem. Art. 13 DSGVO)

Verantwortliche Projektleitung:

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<u>Teil A - Informationen zum Forschungsvorhaben</u>

Liebe Teilnehmer und Teilnehmerinnen,

wir freuen uns sehr über Ihre Teilnahme an unserer <u>Studie zur Eltern-Kind-Interaktion in Spielsituationen</u>. Die Teilnahme an dieser Studie ist freiwillig und unabhängig von der psychotherapeutischen Behandlung in unserer Ambulanz für Kinder- und Jugendlichenpsychotherapie, d.h. eine Psychotherapie ist auch möglich, wenn Sie nicht an dieser Studie teilnehmen. Bevor wir Ihre Daten zum Zweck der Forschung nutzen dürfen, benötigen wir Ihre Einwilligung. Damit Sie diese Entscheidung informiert treffen können und da uns der Schutz Ihrer Daten sehr am Herzen liegt, klären wir Sie in diesem Dokument ausführlich und transparent über die Ziele und den genauen Ablauf der Studie auf und Sie erhalten ausführliche Informationen zu den im Zuge der Studie erhobenen Daten und zur Gewährleistung des Datenschutzes und der Datensicherheit.

<u>1. Ausführliche Beschreibung des Forschungsvorhabens & Inhalt und Zweck der Studie</u>

Das Forschungsvorhaben ist ein Projekt der Lehr- und Forschungseinheit Klinische Psychologie des Kindes- und Jugendalters & Beratungspsychologie und der Psychotherapeutischen Hochschulambulanz für Babys, Kinder, Jugendliche und (werdende) Eltern am Department Psychologie der LMU München. Die Studie untersucht, wie Eltern oder andere Bezugspersonen und ihre Kinder in alltagsnahen, vorab festgelegten Spielsituationen miteinander umgehen. Dabei interessiert uns besonders, wie sich der Kontakt und Umgang zwischen Elternteil und Kind in verschiedenen Spielsituationen unterscheidet und wie dies mit dem familiären Zusammenleben sowie der psychischen Gesundheit der Elternteile/Bezugspersonen und Kinder zusammenhängt.

In den Spielsituationen in dieser Studie wird jeweils ein Elternteil/Bezugsperson mit Kind gebeten, nacheinander zwei Spiele zu spielen. Die Spielsituationen sind für alle Teilnehmenden gleich gestaltet: Sie dauern jeweils 5 Minuten, folgen feste Spielanleitungen und finden unter gleichen Rahmenbedingungen statt. Vor, nach und zwischen den Spielsituationen bitten wir die Elternteile bzw. Bezugspersonen, jeweils einen kurzen Fragebogen auszufüllen. Die Spielsituationen werden auf Video aufgezeichnet und anschließend wissenschaftlich ausgewertet. Dabei werden in der Forschung verbreitete und allgemein anerkannte Methoden zur Untersuchung von zwischenmenschlichem Verhalten verwendet. Die Auswertung der Videos findet zum einen automatisch mithilfe von Software statt, zum anderen durch geschulte Fachkräfte. Nach der Auswertung der Videos liegen dann sogenannte Verhaltensdaten vor, mithilfe derer anschließend der Umgang und die Interaktion zwischen Elternteil und Kind in den Spielsituationen beschrieben werden können.

Für die Teilnahme an dieser Studie gibt es keine spezifische Aufwandsentschädigung oder finanzielle Vergütung. Durch Ihre Teilnahme leisten Sie einen wertvollen Beitrag für die psychologische Forschung: Konkret erweitern wir durch die in dieser Studie gewonnenen wissenschaftlich basierten Erkenntnisse das gegenwärtige Wissen darüber, wie der alltägliche Umgang zwischen Eltern und Kindern in Zusammenhang steht mit wichtigen Faktoren der kindlichen Entwicklung und psychischen Gesundheit. Die Studienergebnisse können somit dazu beitragen, Maßnahmen zur Vorbeugung sowie zur effektiven Bewältigung von Schwierigkeiten in diesem Bereich zu erweitern, um so die Lebensqualität von Kindern, Jugendlichen und deren Familien nachhaltig zu unterstützen.

<u>2. Betroffener Personenkreis und mögliche Belastungen oder Risiken durch die Studienteilnahme</u>

Der von dieser Studie betroffene Personenkreis umfasst Patienten und Patientinnen der Psychotherapeutischen Hochschulambulanz für Babys, Kinder, Jugendliche und (werdende) Eltern am Department Psychologie der LMU München im Alter von 4 bis 14 Jahren (diagnose-übergreifend) und deren Elternteile bzw. Bezugspersonen (unabhängig von elterlicher Geschlechtsidentität, sexueller Orientierung oder biologischer Verwandtschaft).

Die Spielsituationen umfassen ausschließlich Materialien und Inhalte, die in dieser Form in Familien üblich sind und hohe Verbreitung finden, und sind dadurch sehr alltagsnah/-typisch (z.B. Tierfiguren). Die Spielsituationen dauern jeweils 5 Minuten mit 2 Minuten Pause zum Ausfüllen kurzer Selbstbericht-Fragebögen zwischen den beiden Spielen (Gesamtdauer der Interaktion inkl. Pausen und Instruktion: ca. 20 Minuten). Der Fragebogen vor Beginn der Erhebung dauert max. 25 Minuten.
Die Testleitung verlässt während der Erhebung den Raum und die erhobenen Daten werden allein durch geschultes und zur Verschwiegenheit verpflichtetes Personal verarbeitet. Im Zuge der anschließenden Auswertungen können einzelne Teilnehmer oder Teilnehmerinnen auf den Videoaufzeichnungen oder in den verbalen Äußerungen durch unsere Mitarbeiter oder Mitarbeiterinnen zwar erkannt werden, jedoch sind sämtliche beteiligte Personen zur Verschwiegenheit verpflichtet und die Verarbeitung und Auswertung sämtlicher Daten erfolgt streng vertraulich, sodass keine Informationen an Außenstehende weitergegeben werden. Es entstehen somit keine gesonderten Belastungen oder Risiken durch die Studienteilnahme.

3. Zu erhebende Daten

3.1 Personenbezogene Daten: Diese Kategorie enthält Daten, die es grundsätzlich ermöglichen, Sie als Person direkt zu identifizieren bzw. zu erkennen (vgl. Art. 4 DSGVO).

- Identitäts- und Kontaktdaten: Zum Nachweis Ihrer Einwilligung in die Studienteilnahme und um den Ablauf der Studie zu organisieren, erfassen wir einige persönliche Daten wie Name, Vorname, Geburtsdatum, E-Mail-Adresse und Telefonnummer. Nach Abschluss der Datenerhebung werden diese Daten gelöscht. Die Einwilligungserklärungen werden jedoch dauerhaft aufbewahrt.
- Videoaufzeichnungen: Im Rahmen der Studie werden einmalig Videoaufzeichnungen in unserem Videolabor von Ihnen und Ihrem Kind erstellt (Bild- und Tonaufnahmen), in denen die Gesichter klar zu erkennen und die Stimmen deutlich zu hören sind. Diese Videos werden im Laufe der Studie von speziell dafür ausgebildeten Mitarbeitern und Mitarbeiterinnen des Forschungsprojekts zum einen manuell bzw. händisch, zum anderen automatisch mithilfe eines speziellen Programms, ausgewertet. Das für die Auswertung zuständige Forschungspersonal hat keinen Einblick in sonstige Ihrer Person bzw. Ihrem Kind zugeordnete Studiendaten und ist zur Verschwiegenheit über die Inhalte der Videos verpflichtet. Für die weitere Datenverarbeitung und wissenschaftliche Veröffentlichungen werden ausschließlich die pseudonymisierten Verhaltensdaten aus den Videos verwendet bzw. die im Rahmen von Berechnungen zusammengefassten statistischen Ergebnisse. Die erhobenen Videoaufzeichnungen werden stets auf verschlüsselten und passwortgeschützten Speichermedien/-servern gesichert sowie zugangs-/zugriffsbeschränkt und strikt getrennt von sämtlichen restlichen Daten aufbewahrt, um die Vertraulichkeit Ihrer Videoaufzeichnungen zu gewährleisten.

3.2 Pseudonymisierte bzw. anonymisierte Daten: Diese Kategorie enthält Daten, die Ihnen als Person nur durch Hinzuziehung zusätzlicher Informationen zuzuordnen sind (vgl. Art. 4 DSGVO). Nach Löschung bzw. Vernichtung der entsprechenden zusätzlichen Informationen sind diese Daten als anonymisierte Daten anzusehen, die Ihrer Person nicht (mehr) zuzuordnen sind (vgl. EG 26 DSGVO).

- Verhaltensdaten: Zur Auswertung der Videos nutzen wir verschiedene Methoden, um das Verhalten und den Umgang zwischen einem Elternteil und Kind auf unterschiedliche Weise zu untersuchen:
    - *MEA (Motion Energy Analysis)*: Software-Programm, das automatisch Bewegungen von Personen misst, indem es Unterschiede in der Helligkeit zwischen den einzelnen Bildern (Frames) eines Videos erkennt.
    - *CIB (Coding Interactive Behavior)*: Speziell geschultes Personal beschreibt das Verhalten und die Gefühlsausdrücke zwischen Elternteil und Kind im Video gemäß genau vorgegebener Anleitungen und Regeln (standardisiertes Manual).
    - *FEA (Facial Expression Analysis)*: Software-Programm, welches automatisch den emotionalen Gesichtsausdruck bzw. einzelne Ausdrücke in der menschlichen Mimik (z.B. Lächeln) misst.
- Selbstbericht-Daten: Vor, nach und zwischen den Spielsituationen werden Selbstbericht-Daten mittels kurzer Fragebögen erfasst. Die Angaben in diesen Fragebögen werden pseudonymisiert gespeichert und getrennt von den Identitäts- und Kontaktdaten gespeichert.
    - *Soziodemografische Angaben*: Alter (Elternteil und Kind), Geschlecht (Elternteil und Kind), Bildungsstand, aktuelle Berufstätigkeit, Familiensituation. Diese Angaben helfen uns, unsere Stichprobe (Gruppe aller Studienteilnehmenden) übergreifend zu beschreiben. Außerdem ermöglichen sie uns, andere Faktoren zu berücksichtigen, die die Studienergebnisse beeinflussen könnten. So können wir die Fragestellung(en) der Studie beantworten, ohne dass unbeachtete Einflüsse die Ergebnisse verfälschen.
    - *Psychologische Fragebögen*: Wissenschaftlich geprüfte und bewährte Fragebögen zu den Themen psychische Gesundheit (Elternteil und Kind), erlebter Stress, psychische Gesundheit und Wohlbefinden, familiäre Beziehungen, Interaktion und Erziehung.
    - *Angaben zur laufenden psychotherapeutischen Behandlung*: Vergebene Diagnosen im Rahmen der aktuellen Behandlung; bisherige Dauer der aktuellen Behandlung; Behandlungen und Diagnosen in

Vorgeschichte. Diese Angaben dienen ebenfalls dazu, unsere Stichprobe übergreifend zu beschreiben und um sicherzustellen, dass unbeachtete Einflüsse die Studienergebnisse nicht verfälschen.

4. Analyseergebnisse der Daten

Die im Rahmen der Datenerhebung und -verarbeitung gewonnenen Daten (Selbstbericht-Daten, im Rahmen der Videoauswertung beschriebene Verhaltensdaten) werden über alle Teilnehmenden hinweg zusammengefasst (Bildung von Kategorien, Berechnen von Summen und Mittelwerten, etc.) für darauf aufbauende statistische Analysen (Vergleiche der verschiedenen Spielsituationen). In diesen Analysen werden allein solche zusammengefassten Daten verwendet, ohne dass die für die Analysen zuständigen Mitarbeiter und Mitarbeiterinnen nachvollziehen können, welche Werte einer bestimmten Person zuzuordnen sind oder wie bestimmte einzelne Personen auf bestimmte Fragen geantwortet haben. Bei diesen Analysen sind individuelle Ergebnisse und konkrete Werte einzelner Personen nicht von Interesse, sondern allein die übergeordneten Zusammenhänge innerhalb der Gesamtstichprobe aller Teilnehmenden. Aus den Ergebnissen der Analysen, die im Rahmen von Fachartikeln, Konferenzbeiträgen oder Buchkapiteln veröffentlicht werden, kann niemand einen Rückschluss auf einzelne Personen ziehen.

5. Lagerung und Weitergabe von Daten (und technische und organisatorische Maßnahmen gemäß DSGVO)

Ihre in der Studie erhobenen Daten, sowie alle anderen vertraulichen Informationen unterliegen den Bestimmungen der Europäischen Datenschutzgrundverordnung (EU-DSGVO). Die technischen und organisatorischen Maßnahmen (TOMs) zur Sicherstellung des Schutzes Ihrer personenbezogenen Daten im Rahmen dieser Studie beinhalten:

- Pseudonymisierung bzw. Anonymisierung gemäß Art. 4 bzw. EG 26 DSGVO (z.B. Studien-IDs und Archiv-IDs)
- Verschlüsselung (nach AES-256-Bit Standard) und Speicherkontrollen nach zentralen Vorgaben
- Zugangs- und Datenträgerkontrollen (z.B. Transponder- und Schlüsselsystem für den Zugang zu Verarbeitungs-PCs, Login mit individueller ID und Passwort)
- Benutzer- und Zugriffskontrollen (z.B. zentrale Verwaltung von Zugriffsrechten auf Server, etc.)
- Übertragungskontrollen (z.B. Dokumentation der Datenempfänger/innen und Löschfristen)
- Eingabekontrollen (z.B. Protokollierung und Berechtigungskonzept)
- Transportkontrollen (z.B. sichere Transportkanäle)
- Wiederherstellbarkeit & Verfügbarkeitskontrolle (z.B. regelmäßige bzw. automatisierte Backup-Prozesse)
- Datenintegrität & Zuverlässigkeit (z.B. Firewalls und zentrale IT-Sicherheitsmaßnahmen)
- Trennbarkeit (z.B. separate Speicherorte und Schlüsseldateien)
- Überprüfung der Wirksamkeit (z.B. zentrale Dokumentation, Schulungen und Verpflichtung)
- Privacy-by-Design (z.B. einfacher Widerruf)
- Incident-Response-Management (z.B. Dokumentation und Meldung von Datenpannen)

Eine Weitergabe von Studiendaten an am Projekt unbeteiligte Personen oder Außenstehende erfolgt nur in pseudonymisierter bzw. anonymisierter Form, also ohne Weitergabe von Identitätsdaten bzw. ohne Möglichkeit der Zuordnung der Daten zu einzelnen Personen.

6. Beteiligte, Datenflüsse und speichernde Stellen

6.1 Beteiligte datenerhebende/-verarbeitende Institutionen und verantwortliche Personen:

- Ludwig-Maximilians-Universität München
  Klinische Psychologie des Kindes- und Jugendalters & Beratungspsychologie
  Leopoldstraße 13, 80802 München
  - Verantwortliche Projektleitung: Dr. Anton Marx
  - Kontakt: Leopoldstraße 13, 80802 München, anton.marx@psy.lmu.de, 0049 (0) 2180 9513

6.2 Datenempfangende Institutionen:

- Center for Open Science (COS) und Online-Plattform Open Science Framework (OSF)
  - Anschrift: 210 Ridge McIntire Road, Suite 500, Charlottesville, VA 22903-5083, USA
  - Kontakt: contact@cos.io bzw. https://cos.io/
  - Daten: Anonymisierte Studiendaten
- Leibniz Institute for Psychology (ZPID) und Online-Plattform Research Data Center (RDC)/PsychData
  - Anschrift: Universitätsring 15, 54296 Trier, Deutschland
  - Kontakt: info@leibniz-psychology.org bzw. https://leibniz-psychology.org/
  - Daten: Anonymisierte Studiendaten

7. Konkrete Dauer der Speicherung und Löschung der Daten

7.1 Personenbezogene Daten: Die zum Zweck des Studienmanagements erhobenen Identitäts-/Kontaktdaten werden nach Abschluss der Datenerhebung vernichtet. Sobald keine Daten von weiteren Teilnehmenden für die Studie erhoben werden, werden die Videos gemäß der aktuellen Empfehlung der Deutschen Forschungsgemeinschaft (DFG Leitlinien zur Sicherung guter wissenschaftlicher Praxis, 2019, aktuelle Version 2022, Leitlinie 17) für den Zeitraum von 10 Jahren aufbewahrt und anschließend gelöscht. Die unterschriebenen Einwilligungserklärungen (mit Name, Vorname, Geburtsdatum und ggfs. Emailadresse der Teilnehmer und Teilnehmerinnen) werden zur Erfüllung der Rechenschaftspflicht (nach Art. 7 Abs. 1 DSGVO) streng vertraulich und getrennt von sämtlichen erhobenen und verarbeiteten Studiendaten bis zum Zeitpunkt der vollständigen Anonymisierung der Daten aufbewahrt. Nach der vollständigen Anonymisierung der Studiendaten werden auch die Einwilligungserklärungen vernichtet. Die erfolgte Löschung der personenbezogenen Daten wird protokolliert und kann auf Anforderung nachgewiesen werden.

7.2 Pseudonymisierte bzw. anonymisierte Daten: Die pseudonymisierten bzw. anonymisierten Studiendaten und Studienergebnisse werden auf universitären Datenservern bzw. wissenschaftlichen Online-Plattformen in elektronischer Form unbefristet gespeichert (keine Löschung vorgesehen). Damit folgen wir den Empfehlungen der Deutschen Forschungsgemeinschaft (DFG), die Qualität in der Forschung durch die Nachprüfbarkeit wissenschaftlicher Ergebnisse und durch die Möglichkeit zur erneuten Nutzung der Daten zu sichern. Der Zweck, die Art und der Umfang einer möglichen Nachnutzung dieser Daten können aktuell noch nicht genau abgesehen werden. Da die anonymisierten Daten nicht mehr personenbezogen sind und keiner Person zugeordnet werden können, ist eine nachträgliche Löschung auf Wunsch von Teilnehmenden nicht möglich.

8. Pseudonymisierungsverfahren

8.1 Studien-ID: Jedem Teilnehmer bzw. jeder Teilnehmerin wird eine eigene nicht-sinntragende numerische Studien-ID zugewiesen. Diese dient dazu, die verschiedenen, im Rahmen der Studie gesammelten Daten einer Person zu verknüpfen, zu speichern und auszuwerten. Ihre Identitäts- und Kontaktdaten werden somit zu keinem Zeitpunkt direkt mit den erhobenen Daten verbunden. Auch die Videoaufzeichnungen werden für die Auswertung unter der Studien-ID gespeichert. Sie werden entweder automatisch von einer Software oder manuell von geschulten Mitarbeitenden ausgewertet. Aus den Videos werden so Zahlenwerte und Verhaltensdaten gewonnen, die für die Analyse genutzt werden. Nach Abschluss der Datenverarbeitung werden diese Verhaltensdaten, ebenfalls unter der Studien-ID, in Form von Textdateien oder Tabellen gespeichert und getrennt von den Videoaufzeichnungen aufbewahrt.

8.2 Archiv-ID: Nach Abschluss der Auswertung der Videos werden die Videoaufzeichnungen getrennt von den restlichen erhobenen Daten und den Einwilligungserklärungen unter der Verwendung einer eigenständigen und nicht-sinntragenden Archiv-ID abgespeichert (die jeweilige unter der Studien-ID gesicherte Videodatei, siehe Punkt 8.1, wird dabei gelöscht). Diese Archiv-ID erhalten Sie von uns schriftlich nach Ende der Videoaufzeichnung ausgehändigt (siehe Teil B in diesem Dokument), mit der Bitte, diese Archiv-ID gut aufzubewahren, um eine gezielte Löschung Ihrer Videoaufzeichnung zu ermöglichen. Die so archivierten Videoaufzeichnungen werden gemäß der aktuellen Empfehlung der Deutschen Forschungsgemeinschaft (DFG Leitlinien zur Sicherung guter wissenschaftlicher Praxis, 2019, aktuelle Version 2022, Leitlinie 17) für den Zeitraum von 10 Jahren aufbewahrt und anschließend gelöscht.

8.3 Schlüssel-Datei "Zuordnungs-Tabelle": Um mögliche Fehler in den anonymisierten Zahlenwerten zurückverfolgen und korrigieren zu können (vgl. Art. 5 DSGVO zur Sicherstellung der Richtigkeit von Daten), gibt es eine sogenannte Schlüssel-Datei ("Zuordnungs-Tabelle"). Diese Datei enthält die Verknüpfung zwischen den Archiv-IDs und den Studien-IDs, jedoch keine persönlichen Daten wie Name oder Kontaktinformationen. Nur die Studienleitung hat Zugriff auf diese Datei. Diese Schlüssel-Datei wird streng vertraulich, verschlüsselt und passwortgeschützt sowie getrennt von sämtlichen restlichen Daten und Einwilligungserklärungen aufbewahrt. Sobald keine weiteren Daten mehr für die Studie erhoben werden bzw. die Auswertung der Videos abgeschlossen ist, wird die Schlüsseldatei gemäß der aktuellen Empfehlung der Deutschen Forschungsgemeinschaft (DFG Leitlinien zur Sicherung guter wissenschaftlicher Praxis, 2019, aktuelle Version 2022, Leitlinie 17) für den Zeitraum von 10 Jahren aufbewahrt und anschließend gelöscht. Von diesem Zeitpunkt an, kann aus den verbleibenden Zahlenwerten (Selbstbericht- und Verhaltensdaten) kein Rückschluss mehr auf einzelne Personen gezogen werden. In anderen Worten, Ihre Daten sind nach der Vernichtung dieser Schlüssel-Datei vollständig anonymisiert.

9. Rechtsgrundlagen

Die Rechtsgrundlage zur Verarbeitung der beschriebenen personenbezogenen Daten zu verschiedenen Zwecken bildet die Einwilligung gemäß Art. 6 (1) Buchstabe a EU-DSGVO in Teil C dieses Dokuments.

10. Widerruf seitens der Betroffenen

Die Teilnahme an dieser Studie ist freiwillig und Sie haben jederzeit das Recht, die datenschutzrechtliche Einwilligung formlos und ohne Angabe von Gründen zu widerrufen. Durch den Widerruf der Einwilligung wird die Rechtmäßigkeit der aufgrund der Einwilligung bis zum Widerruf erfolgten Verarbeitung nicht berührt (Widerruf mit Wirkung für die Zukunft). Daten, die bereits in wissenschaftliche Auswertungen, Publikationen oder Statistiken etc. eingeflossen sind, können i.d.R. nicht rückwirkend herausgenommen bzw. gelöscht werden. Der Widerruf ist an die Projektleitung zu richten (per Email an Dr. Anton Marx, anton.marx@psy.lmu.de). Ihre Studienteilnahme wird durch den Widerruf beendet und nach Eingang des Widerrufs werden die personenbezogenen Daten gelöscht, solange Ihre Daten in pseudonymisierter Form (d.h. mit Studien-ID) vorliegen. Durch Mitteilung Ihrer Archiv-ID können Sie auch jederzeit die gezielte Löschung Ihrer Video-Aufzeichnung veranlassen. Ihnen entstehen durch den Widerruf keine Kosten oder anderweitige Nachteile.

11. Namen, Kontaktdaten der Verantwortlichen

Die Verantwortung für die Erhebung und Verarbeitung der personenbezogenen Daten liegt bei:

- Verantwortliche Projektleitung:
  Dr. Anton Marx, 0049 (0) 89 2180 9513, anton.marx@psy.lmu.de
  Ludwig-Maximilians-Universität München, Fakultät 11, Department Psychologie
  Lehr- und Forschungseinheit Klinische Psychologie des Kindes- und Jugendalters
  Leopoldstraße 13, 80802 München
- Ansprechperson bei Fragen: Dr. Anton Marx, 0049 (0) 89 2180 9513, anton.marx@psy.lmu.de

12. Hinweis auf Rechte der Betroffenen und Kontaktdaten des Datenschutzbeauftragten

Gemäß Art. 13 II b DSGVO haben die Teilnehmer und Teilnehmerinnen das Recht auf Auskunft (Art. 15 DSGVO, § 34 BDSG), Widerspruch (Art. 21 DSGVO, § 36 BDSG), Datenübertragbarkeit (Art. 20 DSGVO), Löschung (Art. 17 DSGVO, § 35 BDSG), Einschränkung der Verarbeitung (Art. 18 DSGVO) und Berichtigung (Art. 16 DSGVO):

- Möchten Sie eines dieser Rechte in Anspruch nehmen, wenden Sie sich bitte an den behördlichen Datenschutzbeauftragten der LMU München:
  Dr. jur. Marco Wehling, Telefon: 0049 (0) 89 2180 2414, E-Mail: datenschutz@verwaltung.uni-muenchen.de
- Ferner haben Sie das recht, Beschwerde bei der zuständigen Aufsichtsbehörde einzulegen:
  Bayerisches Landesamt für Datenschutzaufsicht, Promenade 27, 91522 Ansbach, Telefon: 0049 (0) 981 53 1300, E-Mail: poststelle@lda.bayern.de, Beschwerdeformular: www.lda.bayern.de/de/beschwerde.html

LMU LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN | KLINISCHE PSYCHOLOGIE DES KINDES- UND JUGENDALTERS & BERATUNGSPSYCHOLOGIE

Studie zur Eltern-Kind-Interaktion in Spielsituationen

Datenschutzrechtliche Aufklärung u. Einwilligung (inkl. Informationen gem. Art. 13 DSGVO)

Teil B - Vergabe der Archiv-ID

Hiermit erhalten Sie die Archiv-ID, unter der die heute von Ihnen erhobene Videoaufzeichnung (Bild- und Tonaufnahmen) nach Abschluss der Datenerhebung bzw. der Kodierung der Videodaten getrennt von den restlichen erhobenen Daten, den Kontaktinformationen, den Einwilligungserklärungen und den ausgewerteten Ergebnissen mit dem Zweck der Archivierung gespeichert werden.

Falls Sie die heute erhobene Videoaufzeichnung löschen lassen möchten, schreiben Sie eine Email an die Studienleitung (Dr. Anton Marx, anton.marx@psy.lmu.de) unter Angabe Ihrer unten stehenden Archiv-ID.

Falls Sie Interesse an den Ergebnissen der Studie haben oder generell Fragen und Anmerkungen, können Sie sich selbstverständlich gerne bei der Studienleitung melden (Dr. Anton Marx, anton.marx@psy.lmu.de).

Archiv-ID:

____

Auf den nächsten Seiten folgt die Einwilligungserklärung (Teil C des Dokuments) mit den Unterschriften der Teilnehmer und Teilnehmerinnen sowie der Testleitung.

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Teil C - Einwilligungserklärung

Teilnehmendes Elternteil bzw. teilnehmende Bezugsperson

Name	Vorname	Geburtsdatum

Teilnehmender Patient bzw. teilnehmende Patientin

Name	Vorname	Geburtsdatum

Einwilligung in die freiwillige Studienteilnahme und die Erhebung, Verarbeitung und Auswertung der Daten

1. Ich habe die Informationen zur Studie gelesen, wurde vollständig über den Ablauf und die Bedeutung der Studie sowie den Datenschutz informiert, hatte die Möglichkeit Fragen zu stellen und mir ist bekannt, dass ich die Studie jederzeit und ohne Angabe von Gründen und ohne negative Konsequenzen abbrechen darf. Ich bin darüber aufgeklärt worden, dass im Rahmen der Videoaufzeichnungen mein Gesicht und das Gesicht meines Kindes klar zu sehen sowie meine Stimme und die Stimme meines Kindes klar zu hören und damit wiedererkennbar ist. Ich wurde über die Folgen eines Widerrufs der datenschutzrechtlichen Einwilligung aufgeklärt, und habe ein schriftliches Exemplar dieser Aufklärung und Einwilligung sowie die individuelle Archiv-ID erhalten.

○ Ja ○ Nein

2. Hiermit willige ich freiwillig ein, dass die aufgezeichneten Videos und die erhobenen Selbstbericht-Daten gespeichert und für wissenschaftliche Auswertungen sowie Veröffentlichungen verarbeitet werden dürfen.

○ Ja ○ Nein

3. Hiermit willige ich freiwillig ein in die Bereitstellung der vollständig anonymisierten Daten in einer der in Teil A dieses Dokuments genannten wissenschaftlichen Onlineplattformen und in deren wissenschaftliche Nachnutzung.

○ Ja ○ Nein

Einwilligung in die sonstige Verwendung der Videoaufzeichnungen und der erhobenen Fragebogendaten

4. Hiermit willige ich freiwillig ein in die zeitlich unbefristete Nutzung der erhobenen Videoaufzeichnungen und Fragebogendaten sowie der aus den Kodierungen gewonnen Interaktions- und Verhaltensdaten auf wissenschaftlichen Symposien und Kongressen mit dem Zweck der Veranschaulichung der Studie und der Analyse-Ergebnisse (Präsenz- oder Online-Veranstaltungen). Bei all diesen Veranstaltungen ist es verboten zu filmen oder sonstige Aufnahmen zu tätigen und sämtliche Teilnehmenden werden zur Verschwiegenheit verpflichtet.

O Ja O Nein

Unterschriften

Elternteil 1
(bzw. Sorgeberechtigte/r 1) *Name, Vorname* *Ort, Datum, Unterschrift*

O Sie dürfen mich unter folgender Emailadresse für mögliche Folgestudien kontaktieren: ____________

Elternteil 1
(bzw. Sorgeberechtigte/r 1) *Name, Vorname* *Ort, Datum, Unterschrift*

O Sie dürfen mich unter folgender Emailadresse für mögliche Folgestudien kontaktieren: ____________

Patient/Patientin *Name, Vorname* *Ort, Datum, Unterschrift*

Testleitung *Name, Vorname* *Ort, Datum, Unterschrift*

Herzlichen Dank für Ihre Teilnahme und wir wünschen Ihnen alles Gute!

Appendix II - NICE Toolbox Manual

How to Analyze a new video/videos

1. Adding new video/videos under your datasets
   - Under D:\datasets\lmu_infant_lab create a new folder.
   - The folder name will be the name of your video. Rename your video as cam0.mp4.

Example:

See: 1.adding_new_video2datasets.mp4

2. Updating calibration file

See: 2.updating_calibration_file.mp4

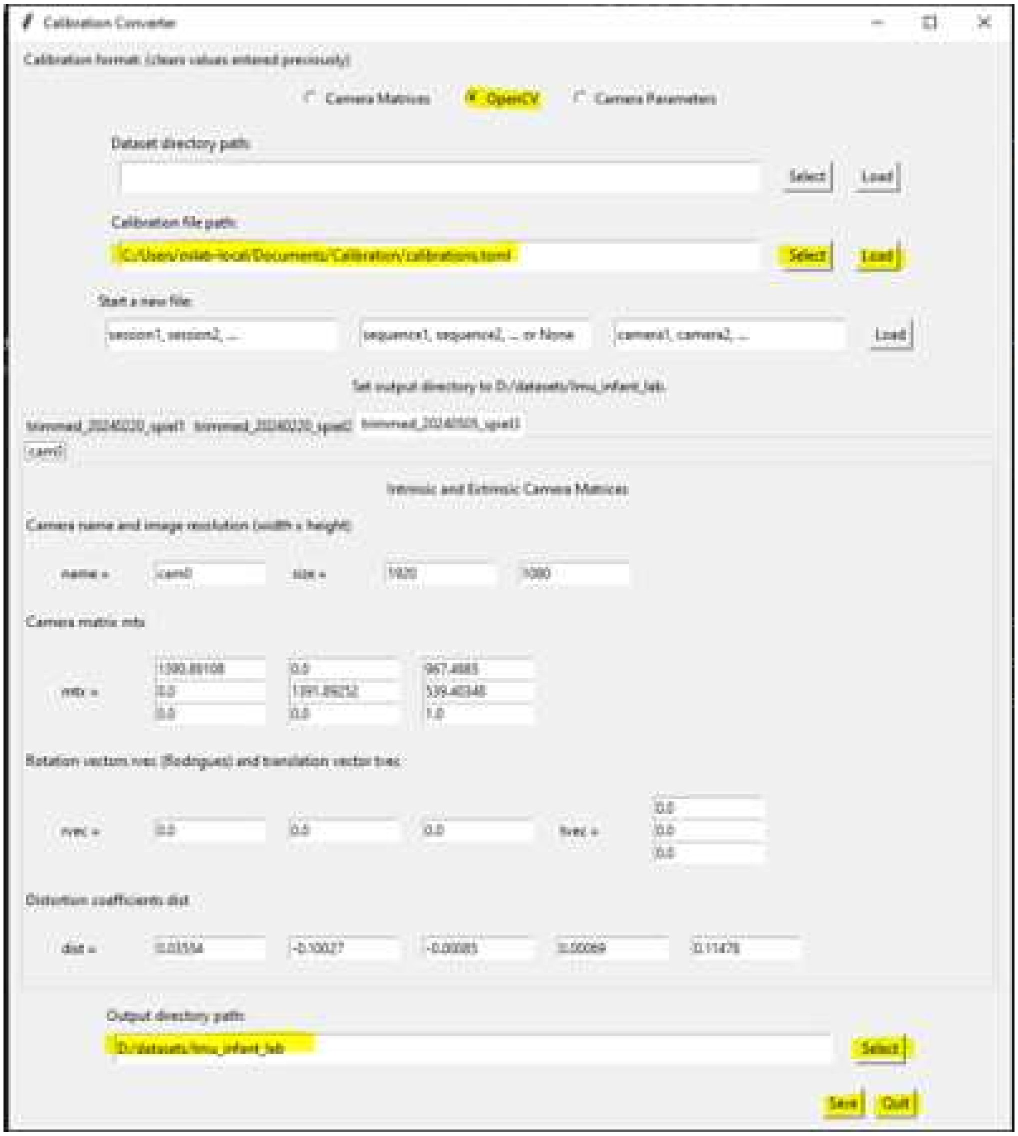
- Open ‘calibrations.toml’ which is located in C:\Users\oslab-local\Documents\Calibration.
- Copy and paste one of the video information. And rename the video. If you want to run more than one video at a time, do the same for each video.
- Open nicetoolbox folder in Visual Studio Code (after open Visual Studio Code click File/Open Folder/select nicetoolbox)
- Open a new terminal in Visual Studio Code (click Terminal)
- Activate environment: Type envs\nicetoolbox\Scripts\activate & Enter
- Type run_calibration_gui & Enter

```
C:\Users\oslab-local\Documents\nicetoolbox>envs\nicetoolbox\Scripts\activate

(nicetoolbox) C:\Users\oslab-local\Documents\nicetoolbox>run_calibration_gui
```

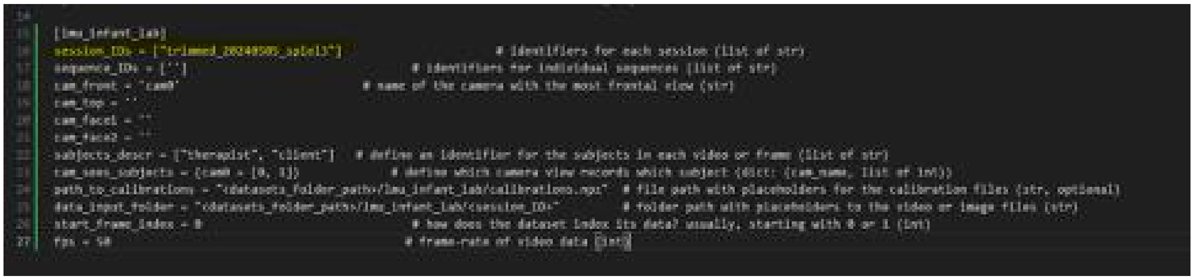
- This will open Calibration Converter Gui
- Select calibration.toml for Calibration File Path
- Click OpenCV
- Load the calibration.toml
- Select Output directory path as D:\datasets\lmu_infant_lab

- Save & Quit



3. Updating Config files
See: 3.updating_config_files

- Open Visual Studio Code
- Open nicetoolbox folder in Visual Studio Code, if it is not already opened.
- Under configs open datasets_properties.toml add the name of your new video into session_IDs (you can keep the other session IDs or overwrite them). If you want to run more than one video, the name of each session should be added here.



```
[lmu_infant_lab]
session_IDs = ["trimmed_20240505_spiel3"]                # identifiers for each session (list of str)
sequence_IDs = ['']                     # identifiers for individual sequences (list of str)
cam_front = 'cam0'                   # name of the camera with the most frontal view (str)
cam_top = ''
cam_face1 = ''
cam_face2 = ''
subjects_descr = ["therapist", "client"]   # define an identifier for the subjects in each video or frame (list of str)
cam_sees_subjects = {cam0 = [0, 1]}            # define which camera view records which subject (dict: {cam_name, list of int})
path_to_calibrations = "<datasets_folder_path>/lmu_infant_lab/calibrations.npz"  # file path with placeholders for the calibration files (str, optional)
data_input_folder = "<datasets_folder_path>/lmu_infant_lab/<session_ID>"         # folder path with placeholders to the video or image files (str)
start_frame_index = 0                          # how does the dataset index its data? usually, starting with 0 or 1 (int)
fps = 50                                      # frame-rate of video data (int)
```

- Under configs open detectors_run_file.toml – Under [run.lmu_infant_lab] give the new session ID/s, and video length.
  - If you want to run more than one video, create a separate dictionary {session_ID = "trimmed_20240220_spiel1", sequence_ID='', video_start = 0, video_length = 1000}, for each video.
  - For video length, the number of frames should be given. For example, if you have a 5 minute 10 seconds video, the maximum video length can be calculated as follows:
    - Your video in seconds: 5 X 60 = 300 seconds + 10 seconds = 310 seconds
    - Since your video's frame per seconds rate is 50, in total you have 310*50=15500 frames.

Additional Notes:

- Currently, I sent it up only for body_joints, kinematics, and proximity components. Since you have only one camera view, and it sees the individuals from side view, the output of other components seem a bit off.
- If you need to run faster, you can set visualize parameter to false.
- Your output folder is defined as D:\outputs\experiments – By default each run creates a new folder under it with the current date. If you want to change this you can change experiment_name parameter

```
detectors_run_file.toml
# This config supports using placeholders.
# options are <git_hash> <commit_message> <me> <today> <yyyymmdd> <time> <pwd>
# and all keys from your local 'machine_specific_paths.toml' as well as 'io'
# and top layer dictionary entries

git_hash = "<git_hash>"
visualize = true            # whether to save image/video visualizations of detectors
save_csv = true             # whether to save all results to csv-files

# each component can be assigned to / run with multiple different algorithms
[component_algorithm_mapping]
gaze_individual = ['multiview_eth_xgaze']
gaze_interaction = ['gaze_distance']
body_joints = ['hrnetw48', 'vitpose']
hand_joints = ['hrnetw48']
face_landmarks = ['hrnetw48']
kinematics = ['velocity_body']
proximity = ['body_distance']
leaning = ['body_angle']
emotion_individual = ['py_feat']

# define which data to run on
[run]
[run.lmu_infant_lab]
components = ["body_joints", "kinematics", "proximity"] # "gaze_individual", "gaze_interaction", "emotion_individual"
videos = [
   {session_ID = "trimmed_20240505_spiel3", sequence_ID='', video_start = 0, video_length = 15455},
]

[io]
experiment_name = "<yyyymmdd>"                                        # define the name of the experiment (str), default: date as "<yyyymmdd>"
out_folder = "<output_folder_path>/experiments/<experiment_name>"  # define where to save the experiment output (str)
out_sub_folder = "<out_folder>/<dataset_name>_<session_ID>_s<video_start>_l<video_length>"
dataset_properties = "configs/dataset_properties.toml"
detectors_config = "configs/detectors_config.toml"
assets = "<code_folder>/nicetoolbox/detectors/assets"
```

- In the example video, the therapist was at the left side, and the client was on the right side of the video. If this is different for some videos, before running those videos change subject_description in dataset_properties.toml. For example, if on this video the client is on the right side, then it should be [“client”, “therapist”]

```
configs > dataset_properties.toml
[communication_multiview]
session_IDs = ["session_xyz"]                  # identifiers for each session (list of str)
sequence_IDs = ['']                            # identifiers for individual sequences (list of str)
cam_front = 'view_center'                      # name of the camera with the most frontal view (str)
cam_top = 'view_top'                           # camera name of a frontal view from top (str, optional)
cam_face1 = 'view_left'                        # camera name of a view of one subject's face (str, optional)
cam_face2 = 'view_right'                       # camera name of a view of a second subject's face (str, optional)
subjects_descr = ["person_left", "person_right"]   # define an identifier for the subjects in each video or frame (list of str)
cam_sees_subjects = {view_center = [0, 1], view_top = [0, 1], view_left = [0], view_right = [1]}          # define which camera view records which subject (dict: (cam_name, list of int))
path_to_calibrations = "<datasets_folder_path>/communication_multiview/calibrations.npz"  # file path with placeholders for the calibration files (str, optional)
data_input_folder = "<datasets_folder_path>/communication_multiview/<session_ID>"        # folder path with placeholders to the video or image files (str)
start_frame_index = 0                          # how does the dataset index its data? usually, starting with 0 or 1 (int)
fps = 30                                       # frame-rate of video data (int)

[lmu_infant_lab]
session_IDs = ["trimmed_20240505_spiel3"]                 # identifiers for each session (list of str)
sequence_IDs = ['']                            # identifiers for individual sequences (list of str)
cam_front = 'cam0'                   # name of the camera with the most frontal view (str)
cam_top = ''
cam_face1 = ''
cam_face2 = ''
subjects_descr = ["therapist", "client"]  # define an identifier for the subjects in each video or frame (list of str)
cam_sees_subjects = {cam0 = [0, 1]}          # define which camera view records which subject (dict: (cam_name, list of int))
path_to_calibrations = "<datasets_folder_path>/lmu_infant_lab/calibrations.npz"  # file path with placeholders for the calibration files (str, optional)
data_input_folder = "<datasets_folder_path>/lmu_infant_lab/<session_ID>"        # folder path with placeholders to the video or image files (str)
start_frame_index = 0                          # how does the dataset index its data? usually, starting with 0 or 1 (int)
fps = 30                                      # frame-rate of video data (int)
```

4. Run Nicetoolbox

see: 4.run_nicetoolbox.mp4

- Open a new terminal in Visual Studio Code (click Terminal)
- Activate environment: Type envs\nicetoolbox\Scripts\activate & Enter
- Type run_detectors & Enter

5. Visualize outputs using Rerun Visualizer

see: 5.visualize_output_in_rerun.mp4

- Open visualizer_config.toml
- Change the name of experiment_folder
- Change video_name
- Open a new terminal in Visual Studio Code
- Activate environment: Type envs\nicetoolbox\Scripts\activate & Enter
- Type run_visualization & Enter
- Wait until all frames uploaded

Appendix III - Primary Behavioral Observation Notes

Primary Behavioral Observation of Selected NICE videos - Dyads 1-9

1) p1g1

- Mostly all good.
- The child's leg does show more movement than there really is.
    - 0:50-1:10 - when his legs overlap each other the software does get a bit confused.

2) p1g2

- All good, nothing out of place here.
- No overlap.

3) p2g1; p2g2 - unable to process

4) p3g1

- 0:10 experimenter walks by; control for that.
- 0:43 When it's the mother's turn, as she is hitting the block, the stable hand is also showing movement which isn't there. Is that controllable? It's happening because the two hands are overlapping.
- Otherwise all good.

5) p3g2

- 0:00-0:10 Mother's right leg showing some movement that isn't there;
- 0:10-0:20 The child's leg is also moving in the wrong place.
- 3:40-4:07; 4:40-4:46 The child's legs are showing a lot of movement when there isn't any. It seems like the software gets confused when there's overlap, especially when the individual is wearing black. - Note for future experimental sessions.

6) p4g1

- 0:00-0:10 The child's arm shows some unwanted movement.
- 4:50-5:00 The child's hands show unwanted movement when they overlap.

7) p4g2

- 4:00-4:15 nothing major but the child’s knee shows more movement than what there really is.
- Otherwise, a really good video. Could be used for presentations as an example of what visualizations look like.

8) p5g1

- 1:20 The child walks out of frame. Comes back at 1:27 with a soft toy, during structured play?? Control
- 1:33 The child and father overlap, confusing the software. Some unwanted movement but mostly good.
- 4:30 The child walks out of frame, and then the video is no longer concentrated around the game. So the video can be considered ‘trash’ after this.

9) p5g2

- 0:00-0:30 The father’s left arm shows some unwanted movement because it’s behind the box which is confusing the software.
- 2:37-3:15 The child walks out of the frame. Then there is overlap between the dyad which confuses the software.
- 4:05-4:30 The child walks out of frame again.
- 4:30-4:55 The box being in front of the father’s arms confuses the software almost throughout the video but especially the ending.

10) p6g1

- 1:00-1:10 Father gets up to fix daughter’s chair. Their bodies overlap for a fraction of a second.
- 4:20-end The child’s right leg shows constant unwanted movement because it is behind the chair.
- Otherwise, the father’s frame is steady.

11) p6g2

- 1:05-1:15 some unwanted movement in the child's right leg, same as p6g1 but not as much, could be ignored.
- 2:00-2:50same here, unwanted movement in the child’s right leg when it is overlapped by the chair.
- 3:35-4:05 same here.

- 5:00-end same here. The child's legs show a lot of unwanted movement that isn't there all through to the end.

12) p22g1

- Person walks across in the beginning, control
- 3:45-3:55 Some unwanted movement in the child's legs
- 4:00-5:30 Child's legs overlapping with the table confuses the softwares showing lots of unwanted movement.

13) p22g2

- 4:30-end The child gets up and moves towards the mother. When they overlap the software gets confused. The child then goes out of frame and then comes back overlapping the mother.
- Otherwise the video is good. So maybe it can be cut?

14) p23g1

- The video begins with unwanted movement being shown in the mother's legs. Maybe the software is confusing it with the table. Happens continuously from the beginning to the end.
- The child's hand also shows some unwanted movement when it goes behind the box (0:00-0:35)
- Really short video…why?

15) p23g2

- Some unwanted movement in the child's left shoulder in the beginning minute of the video (0:00-1:00)
- When the mother crosses her legs at 2:20, it starts showing some unwanted movement.
- Pretty good otherwise.

16) p24g1

- Very good video - can be used in presentations.
- The only thing is that the child walks out of frame at the end but that is after the structured play ends.

17) p24g2

- Father's right arm showing some unwanted movement when it's covered by the other arm. Throughout the first minute there are short instances where this happens.
- Otherwise a very smooth video.

Appendix IV - Defining a Threshold for the Confidence Score - Observation Notes + Data Analysis for 0.0 & 0.4 thresholds.

Observation Notes:

Dyad Video Name	**bbbox_overlap**	**kinematics_bodydisplacement**	**kinematics_bodyvelocity**	**Notes**
p1g1	**Selected Accurate frames:** 500-550 **Selected Inaccurate frames:** 8900-9000 **Highest amount of overlap:** 0.67 **Frame Number:** 8925 **Observations:** The mother's hand briefly overlaps with the child's but visibly not much. 7% is valid.	**Selected Accurate frames:** 500-550 **Selected Inaccurate frames:** 3400-3500 **Lowest confidence score:** 0.3819 **Frame Number:** 3496 **Observations:** Visibly quite accurate, however the child's legs overlap which might confuse the software, hence the low confidence score. However, when watching the video visualization there is some inaccurate movement being shown even at this confidence score.	**Selected Accurate Frames:** 500-550 **Selected Inaccurate Frames:** 3400-3500 **Lowest confidence score:** 0.3819 **Frame Number:** 3496 **Observations:** Visibly quite accurate, however the child's legs overlap which might confuse the software, hence the low confidence score.	Confidence scores much lower for the child. Possibly because the child moves a lot more than the parent.
p6g2	**Selected Accurate Frames:** 650-700 **Selected Inaccurate frames:** 500-550; 4900-5050 **Highest amount of overlap**: 0.296	**Selected Accurate Frames:** 500-550 **Selected Inaccurate frames:** 17000-17100 **Lowest confidence score:** 0.0169 **Frame Number:** 17035	**Selected Accurate Frames:** 500-550 **Selected Inaccurate frames:** 17000-17100 **Lowest confidence score:** 0.0169 **Frame Number:**	Overall confidence scores very low for certain faulty parts of the video. I visualized other parts of the video with confidence scores of 0.35 (2924). Here, the child's body

	Frame Number: 5009 **Observations:** The child's hand overlaps the fathers elbow. The child's leg is also overlapping the chair. Very minimal visible overlap.	**Observations:** Clearly visible, faults of the softwares. The software is showing the child's knees and ankles to be way higher than they actually are.	17035 **Observations:** Clearly visible, faults of the softwares. The software is showing the child's knees and ankles to be way higher than they actually are.	position looks visibly accurate.
p22g1	**Accurate Frames:** 500-550 **Inaccurate Frames:** 100-200 **Highest amount of overlap:** 0.137 **Frame Number:** 120 Observations: Here, a person walks across the camera before the play situation starts. Therefore, there is a clear overlap and the software is just guessing where the subjects are.	**Accurate Frames:** 500-550 **Inaccurate Frames:** 13500-13700 **Lowest confidence score:** 0.028 **Frame Number:** 13500 Observations: Clearly the software has gotten it wrong here. It is evident that the child's legs aren't where the software deems it to be. The ankles are a lot higher than where they're supposed to be.	**Accurate Frames:** 500-550 **Inaccurate Frames:** 13500-13700 **Lowest confidence score:** 0.028 **Frame Number:** 13500 Observations: Clearly the software has gotten it wrong here. It is evident that the child's legs aren't where the software deems it to be. The ankles are a lot higher than where they're supposed to be.	The selected inaccurate frames clearly represent faults in the software represented by the low confidence scores. When I checked for other halfway points such as when the confidence score is 0.0129 (13532) it is evident that the software is still inaccurate.

Here, we can see how various confidence scores can be compared from a range of these exemplary videos. p1g1, is a video where the software makes very minimal mistakes with the lowest confidence score being 0.388 and there we can see that despite the software being unsure, the positioning is correct. Comparatively, when we look at the lowest confidence scores from the other two videos, of 0.0169 and 0.028 we can see that the software is clearly wrong. In the sense that where the child's actual legs are and where the software thinks they are, is completely wrong, hence, the low confidence score. When I compared other scores of 0.129

and 0.35, it was evident to me that the frame with a 0.129 confidence score is also inaccurate, however the frame with 0.35 confidence score is visually accurate.
In an attempt to further analyse thresholds, we decided to go the opposite way. Searching for the highest possible limit where the data is acceptable and accurate.

p6g2 - 3487 - 0.256 = accurate
p6g2 - 3499 - 0.218 = accurate but a lot of movement in visualizations.
p6g2 - 3751 - 0.189 = accurate frame but when I checked the visualized video there was a lot of movement.

p6g2 - 3819 - 0.141 = accurate
p6g2 - 6768 - 0.099 = inaccurate

p22g1 - 13233 - 0.140 = inaccurate

p5g1 - 17732 - 0.156 = inaccurate

p5g1 - 362 - 0.201 = accurate frames but a lot of movement in the visualizations
p5g1 - 358 - 0.251 = accurate frames but a lot of movement in the visualizations
p5g1 - 371 - 0.122 = accurate frames but a lot of movement in the visualizations
p5g1 - 429 - 0.378 = accurate frames but a lot of movement in the visualizations

p5g1 is a great example to use for pretest. The beginning of the video can see that the software is uncertain and then slowly it settles down showing relatively higher confidence scores from 200-225 and then slowly becomes more and more ‘shaky’ as the confidence scores go down.

So, If we want to maximize the amount of data we have we can go for an exploratory threshold of 20% but if we want to minimize all faulty data we can go for and exploratory threshold of 40%

Data Analysis - 0.0 Threshold:

Sample	Synchrony Type	N	Mean	Median	SD	IQR	Min	Max	Skewness	Kurtosis	Normality	Normality Flag
Full sample	Real synchrony	32	0.052312	0.051278	0.006242	0.006343	0.044024	0.071013	1.156469	1.174692	0.006938	p < .05 (Non-normal)
	Pseudosynchrony	32	0.050786	0.050451	0.006458	0.00639	0.03811	0.066785	0.715523	0.450264	0.077038	p > .05 (Normal)
Structured play	Real synchrony	16	0.051194	0.051231	0.005479	0.005709	0.044024	0.066656	1.072173	1.454419	0.053503	p > .05 (Normal)
	Pseudosynchrony	16	0.049615	0.048589	0.006419	0.005618	0.03811	0.066668	0.722543	0.961706	0.213574	p > .05 (Normal)
Free play	Real synchrony	16	0.053429	0.051504	0.006917	0.008262	0.045067	0.071013	0.997798	0.243579	0.096063	p > .05 (Normal)
	Pseudosynchrony	16	0.051957	0.05069	0.006485	0.007099	0.043424	0.066785	0.70209	-0.384	0.313355	p > .05 (Normal)

Synchrony vs Pseudosynchrony 0.0:

Shapiro_W	Shapiro_p	T_test_t	T_test_df	T_test_p	Wilcox_V	Wilcox_p	Cohens_d
0.885	0.003	4.640	31.000	0.000	489.000	0.000	0.239

Structured Play vs Free Play 0.0:

Shapiro_W	Shapiro_p	T_test_t	T_test_df	T_test_p	Wilcox_V	Wilcox_p	Cohens_d
0.972	0.869	-1.357	15.000	0.195	46.000	0.266	-0.354

Data Analysis - 0.4 Threshold

Sample	Synchrony Type	N	Mean	Median	SD	IQR	Min	Max	Skewness	Kurtosis	Normality	Normality Flag
Full sample	Real synchrony	32	0.052202	0.051223	0.006317	0.005483	0.043217	0.071015	1.089771	1.10868	0.013139	p < .05 (Non-normal)
	Pseudosynchrony	32	0.050684	0.050474	0.006516	0.006543	0.037397	0.066767	0.651796	0.428821	0.109412	p > .05 (Normal)
Structured play	Real synchrony	16	0.05101	0.05107	0.005623	0.004844	0.043217	0.066556	0.940684	1.236406	0.070244	p > .05 (Normal)
	Pseudosynchrony	16	0.049408	0.048444	0.006512	0.005859	0.037397	0.066488	0.646928	0.884891	0.264918	p > .05 (Normal)
Free play	Real synchrony	16	0.053393	0.051912	0.006914	0.008164	0.044874	0.071015	0.991689	0.256167	0.106042	p > .05 (Normal)
	Pseudosynchrony	16	0.051959	0.05134	0.00647	0.00704	0.04355	0.066767	0.679142	-0.39208	0.332039	p > .05 (Normal)

Synchrony vs Pseudosynchrony 0.4:

Shapiro_W	Shapiro_p	T_test_t	T_test_df	T_test_p	Wilcox_V	Wilcox_p	Cohens_d
0.890	0.003	4.688	31.000	0.000	490.000	0.000	0.235

Structured Play vs Free Play 0.4:

Shapiro_W	Shapiro_p	T_test_t	T_test_df	T_test_p	Wilcox_V	Wilcox_p	Cohens_d
0.975	0.907	-1.444	15.000	0.169	44.000	0.224	-0.375

Appendix V - Surrogate Synchrony (SUSY) Notes - Wolfgang Tschacher, 2019.

Description of the algorithm Surrogate Synchrony (SUSY) WT, 24.9.2019
SUSY computes synchrony on the basis of windowed cross-correlations. Synchrony is defined as the correlation (or 'coordination', 'entrainment', 'coupling') of two simultaneously occurring processes. The processes are given as bivariate time series. In a *.txt-file, the time series are in columns, the single measurements are lines. Variable names can be in the header line. It is assumed that the processes are sampled at high frequency, 1 Hz (1/s) or higher. The *.txt-file may contain time series of different durations; the longest time series must be in the first two columns. The missing data of the other columns must be empty; only the separators should be in the file.

(1) Cross-correlations of the bivariate time series are computed up to a specific lag in seconds (s). This is the parameter <Maxlag>. For example, if the process was sampled at 10 Hz (or, a video had 10 frames per second: 10 fps) and <Maxlag> = 5 is chosen, then 101 crosscorrelation values result (because the time series has 100 lags between lag=-5s and lag=5s, plus lag zero). Cross-correlation is performed within a chosen <Segment> of e.g. 30s. The time series is divided into segments without overlap, thus a time series of say five minutes contains ten 30s-segments. All cross-correlations are then aggregated – this is done by transforming correlations to Fisher's Z, using absolute values only, then computing the mean Z in a segment. This is repeated across all segments of the time series. The mean Z of all segments are finally aggregated, yielding the overall mean_Z of the time series. (note: SUSY computation is scale-invariant. Thus, if your time series are sampled at lower frequencies, you may use other time scales. E.g., instead of Hz the unit may be 1/min, and parameters <Maxlag>and <Segment> are accordingly in minutes).

(2) Segment shuffling (segment-wise permutation) is used to create surrogate time series. If a time series contains 10 segments, 10x9=90 different surrogates can be generated. On each surrogate the above computations (1) are run. This delivers a distribution of surrogate mean_Z, hence an effect size <ES> of the 'real' mean_Z against surrogates. Thus SUSY provides two different synchrony measures of each bivariate time series: mean_Z (always a positive number because of the use of absolute values) and ES of mean_Z.
(3) SUSY output contains two different synchrony measures of each bivariate time series: mean Z and ES of mean Z. The respective output variables are <Z>and <ES>. Importantly, the data are also computed without the use of absolute Z ('no-absolutes'): <Z(noAbs)> and <ES(noAbs)>.
If <Automatic> is clicked, the synchrony is computed of all adjacent pairs of columns in the *.txt-file. If <Automatic> is unclicked, you may choose the two columns to be analysed for synchrony, and two plots are additionally prepared.
Plot-ID:

0 = no plot
1 = mean cross-correlations (absolute correlation values); export cross-correlations
2 = synchrony by segment (absolute correlation values)
3 = mean Z cross-correlations (absolute correlation values)
4 = times series plot
5 = mean Z cross-correlations (no-absolute values)
The SUSY algorithm was coded by David Leander Tschacher instructed by Wolfgang Tschacher. If you use SUSY, please cite: Tschacher W & Haken H (2019). The Process of Psychotherapy – Causation and Chance. Cham: Springer Nature.

Appendix VI - Surrogate Synchrony (SUSY) R Package - Wolfgang Tschacher, 2019.

Package ‘SUSY’
July 21, 2025
Version 0.1.0
Title Surrogate Synchrony
Suggests gtools
Description Computes synchrony as windowed cross-correlation based on two-dimensional time series
in a text file you can upload. 'SUSY' works as described
in Tschacher & Meier (2020) <doi:10.1080/10503307.2019.1612114>.
License GPL-2
URL https://wtschacher.github.io/SUSY/
BugReports https://github.com/wtschacher/SUSY/issues
NeedsCompilation no
Author Wolfgang Tschacher [aut, cre],
David Tschacher [ctb],
Jan Gorecki [ctb]
Maintainer Wolfgang Tschacher <wolfgang.tschacher@upd.unibe.ch>
Repository CRAN
Date/Publication 2022-11-24 09:00:13 UTC
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2 as.data.frame.susy
as.data.frame.susy susy to data.frame conversion method
Description
Turns susy class object into a data.frame.
Usage
S3 method for class 'susy'
as.data.frame(x, row.names=NULL, optional=FALSE, corr.no.abs=TRUE, ...)
Arguments
x A susy object.
row.names Ignored, only for consistency to generic as.data.frame method.
optional Ignored, only for consistency to generic as.data.frame method.
corr.no.abs Logical, defaults to TRUE display correlation without the absolute value.

... Ignored.
Value
Returns data.frame.
See Also
susy
Examples
n = 1000
data = data.frame(
var1 = runif(n, 300, 330),
var2 = runif(n, 300, 330)
)
res = susy(data, segment=30L, Hz=15L)
as.data.frame(res)
plot.susy 3
plot.susy susy plot method
Description
Generate plot(s) for a susy object.
Usage
S3 method for class 'susy'
plot(x, type=c(4, 5), ...)
Arguments
x A susy object.
type Numeric, specifies the types of plot, defaults to c(4, 5).
1. GMcrosscorrs
2. synchrony by segments
3. GM-Z
4. time series plot
5. Z not abs
... Ignored.
Details
Method can generate multiple types of plots by providing numeric vector to type argument. Note it
will generate plots for each pair (cross computation) in x, so the final number of plots is length(x) * length(type).
Value
Returns NULL invisibly. Generate plot(s) as a side effect.
See Also
susy
Examples
n = 1000

data = data.frame(
var1 = runif(n, 300, 330),
var2 = runif(n, 300, 330),
var3 = runif(n, 300, 330)
)
res = susy(data, segment=30L, Hz=15L, permutation=TRUE)
plot(res, type=c(3,5))
4 print.susy
print.susy susy print method
Description
Prints information about an susy object.
Usage
S3 method for class 'susy'
print(x, corr.no.abs=TRUE, legacy=FALSE, ...)
Arguments
x A susy object.
corr.no.abs Logical, defaults to TRUE display correlation without the absolute value.
legacy Logical, defaults to FALSE, when TRUE print will produce an output that matches
the output of legacy SUSY implementation.
... Extra arguments passed to print.data.frame method.
Value
Returns x invisibly. Display output to console as a side effect.
See Also
susy
Examples
n = 1000
data = data.frame(
var1 = runif(n, 300, 330),
var2 = runif(n, 300, 330)
)
res = susy(data, segment=30L, Hz=15L)
res
print(res, corr.no.abs=FALSE)
print(res, digits=4)
print(res, legacy=TRUE)
susy 5
susy Surrogate Synchrony
Description
Cross-correlations of two time series are computed up to a specific lag in seconds maxlag. Crosscorrelation

is done within segment of the time series. The size of segments segment can be chosen
in seconds. Aggregation is then performed by transforming correlations to Fisher's Z, computing mean Z in each segment, then across all segments of the time series. Segment shuffling is used to create surrogate time series, on which the same computations are run. This provides effect sizes ES. SUSY provides these different synchrony measures for each twin time series: mean Z and ES of
mean Z; mean absolute_Z and ES of mean absolute_Z.

Usage

susy(x, segment, Hz, maxlag=3L, permutation=FALSE,
restrict.surrogates=FALSE, surrogates.total=500)

Arguments

x A data.frame of numeric columns.

segment Integer, size in seconds. Must not be smaller than 2 * maxlag, must not be larger than half the the time series (nrow(x)/2).

Hz Integer, frames per second (sampling rate).

maxlag Integer, maximum lag for ccf in seconds. Default 3 seconds.

permutation Logical, default FALSE requires x to have even number of columns which are processed in pairs (1-2, 3-4, etc.). When permutation is TRUE then function computes all pairs combinations between columns provided in x (n*(n-1)/2 pairs).

restrict.surrogates

Logical, default FALSE. Restrict the number of surrogates or not.

surrogates.total

Numeric, the number of generated surrogates, default 500. Ignored when restrict.surrogates is FALSE (default).

Details

Segments are non-overlapping, and the number of segments that fit into the time series may have a
remainder (usually a few seconds at the end of the time series), which is not considered.

Value

Object of class susy is returned. Each cross correlation pair is an element in resulting object.

See Also

plot.susy, as.data.frame.susy, print.susy

6 susy

Examples

n = 1000
data = data.frame(
var1 = runif(n, 300, 330),
var2 = runif(n, 300, 330),
var3 = runif(n, 300, 330)

```
)
## use only first two columns
res = susy(data[, 1:2], segment=30L, Hz=15L)
length(res)
names(res)
## use all columns and permutation
res = susy(data, segment=30L, Hz=15L, permutation=TRUE)
length(res)
names(res)
## print susy
res
print(res, legacy=TRUE)
## plot susy
plot(res)
plot(res, type=1:2)
```

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7

1) R-Script for descriptives table:

```
# Set working directory

setwd("C:/Users/Madhavi/Desktop/msc_nabu_20260122")


# Load packages

library(readxl)
library(dplyr)
library(tidyr)
library(psych)


# Load data

data <- read_excel("raw_data.xlsx") #enter your own raw data

# Clean play situation labels
data$`Play Situation` <- trimws(data$`Play Situation`)


# Convert to long format

data_long <- pivot_longer(
  data,
  cols = c(Z, Z.Pseudo),
  names_to = "Synchrony_Type",
  values_to = "Score"
)

# Rename synchrony labels
data_long$Synchrony_Type <- recode(
  data_long$Synchrony_Type,
  "Z" = "Real synchrony",
  "Z.Pseudo" = "Pseudosynchrony"
)

# FORCE ORDER (Real first) - this puts real synchrony first
```

```
data_long$Synchrony_Type <- factor(
  data_long$Synchrony_Type,
  levels = c("Real synchrony", "Pseudosynchrony")
)


# FULL SAMPLE - this includes all the key descriptives required

full_sample <- data_long %>%
  group_by(Synchrony_Type) %>%
  summarise(
    Sample = "Full sample",
    N = n(),
    Mean = mean(Score),
    Median = median(Score),
    SD = sd(Score),
    IQR = IQR(Score),
    Min = min(Score),
    Max = max(Score),
    Skewness = psych::describe(Score)$skew,
    Kurtosis = psych::describe(Score)$kurtosis,
    Normality = shapiro.test(Score)$p.value,
    .groups = "drop"
  )


# STRUCTURED PLAY - structured play before free play

structured_sample <- data_long %>%
  filter(`Play Situation` == "Structured") %>%
  group_by(Synchrony_Type) %>%
  summarise(
    Sample = "Structured play",
    N = n(),
    Mean = mean(Score),
    Median = median(Score),
    SD = sd(Score),
    IQR = IQR(Score),
    Min = min(Score),
    Max = max(Score),
```

```
    Skewness = psych::describe(Score)$skew,
    Kurtosis = psych::describe(Score)$kurtosis,
    Normality = shapiro.test(Score)$p.value,
    .groups = "drop"
  )

# FREE PLAY

free_sample <- data_long %>%
  filter(`Play Situation` == "Free") %>%
  group_by(Synchrony_Type) %>%
  summarise(
    Sample = "Free play",
    N = n(),
    Mean = mean(Score),
    Median = median(Score),
    SD = sd(Score),
    IQR = IQR(Score),
    Min = min(Score),
    Max = max(Score),
    Skewness = psych::describe(Score)$skew,
    Kurtosis = psych::describe(Score)$kurtosis,
    Normality = shapiro.test(Score)$p.value,
    .groups = "drop"
  )


# Combine tables - this puts all tables together

final_table <- bind_rows(
  full_sample,
  structured_sample,
  free_sample
)


# Add normality interpretation

final_table <- final_table %>%
  mutate(
```

```
    `Normality Flag` = ifelse(
      Normality >= 0.05,
      "p ≥ .05 (Normal)",
      "p < .05 (Non-normal)"
    )
  )


# Rename headings (NO underscores) - remove underscores

colnames(final_table) <- c(
  "Synchrony Type",
  "Sample",
  "N",
  "Mean",
  "Median",
  "SD",
  "IQR",
  "Min",
  "Max",
  "Skewness",
  "Kurtosis",
  "Normality",
  "Normality Flag"
)


# Reorder columns nicely - regoranize everything

final_table <- final_table %>%
  select(
    Sample,
    `Synchrony Type`,
    N,
    Mean,
    Median,
    SD,
    IQR,
    Min,
    Max,
```

```
    Skewness,
    Kurtosis,
    Normality,
    `Normality Flag`
  )


# finalize the table

print(final_table)


# Save table

write.csv(
  final_table,
  "Synchrony Master Descriptives.csv",
  row.names = FALSE
)
```

2) R-script for visualizations

```
# script for overlay Density Curves and Boxplot for Z vs Z.Pseudo

# 1. Set Working Directory

setwd("C:/Users/Madhavi/Desktop/msc_nabu_20260122")


# 2. Load Packages


library(ggplot2)
library(dplyr)
library(tidyr)
library(readxl)


# 3. Load Data
```

```
data <- read_excel("synchrony_data.xlsx")


# 4. Convert to Long Format

data_long <- pivot_longer(
  data,
  cols = c(Z, Z.Pseudo),
  names_to = "Synchrony_Type",
  values_to = "Synchrony_Value"
)

# 5. Overlayed Density Curves (Blue for Z, Pink for Z.Pseudo)

overlay_density <- ggplot(data_long,
                          aes(x = Synchrony_Value,
                              fill = Synchrony_Type,
                              colour = Synchrony_Type)) +
  geom_density(alpha = 0.3, size = 1.2) +  # translucent density curves
  scale_fill_manual(values = c("Z" = "#1f77b4",        # blue fill
                               "Z.Pseudo" = "#ff69b4")) + # pink fill
  scale_colour_manual(values = c("Z" = "#1f77b4",      # blue line
                                 "Z.Pseudo" = "#ff69b4")) + # pink line
  labs(title = "Overlayed Density: Synchrony vs Pseudosynchrony",
       x = "Synchrony Score (Z)",
       y = "Density") +
  theme_minimal()

print(overlay_density)

# Save the overlay density plot
ggsave("Overlay_Density_PinkBlue.png",
       overlay_density,
       width = 7, height = 5)


# 6. Boxplot with Translucent Colors (Blue Z, Pink Z.Pseudo)

box_plot <- ggplot(data_long,
                   aes(x = Synchrony_Type,
```

```
                    y = Synchrony_Value,
                    fill = Synchrony_Type)) +
  geom_boxplot(alpha = 0.4, width = 0.6, outlier.shape = NA) +  # translucent boxes
  geom_jitter(width = 0.1, alpha = 0.6, colour = "black") +     # points with transparency
  scale_fill_manual(values = c("Z" = "#1f77b4",        # blue
                        "Z.Pseudo" = "#ff69b4")) +  # pink
  labs(title = "Boxplot: Synchrony vs Pseudosynchrony",
       x = "Type",
       y = "Synchrony Score (Z)") +
  theme_minimal()

print(box_plot)

# Save the boxplot
ggsave("Boxplot_PinkBlue_Translucent.png",
       box_plot,
       width = 7, height = 5)
```

3) R-Script for Inferentials

```
# Inferential Statistics

# 1. Set working directory

setwd("C:/Users/Nachiket/Desktop/msc_nabu_20260122")  # Change to your folder

# 2. Load required packages

library(readxl)
library(effsize)

# 3. Load your data

# Excel example
data <- read_excel("synchrony_data.xlsx")

# CSV example (if needed)
# data <- read.csv("synchrony_wide.csv")
```

```
# 4. Compute difference scores

# Assuming columns: Z = observed synchrony, Z.Pseudo = pseudosynchrony
data$diff <- data$Z - data$Z.Pseudo

# 5. Test normality of difference scores

shapiro_result <- shapiro.test(data$diff)
print(shapiro_result)

# 6. Paired t-test (parametric)
t_result <- t.test(data$Z, data$Z.Pseudo, paired = TRUE)
print(t_result)

# 7. Wilcoxon signed-rank test (non-parametric)

wilcox_result <- wilcox.test(data$Z, data$Z.Pseudo, paired = TRUE)
print(wilcox_result)

# 8. Compute Cohen's d (dependent samples)

cohen_d_result <- cohen.d(data$Z, data$Z.Pseudo, paired = TRUE)
print(cohen_d_result)

# Optional: Save all results to a CSV

results <- data.frame(
  Shapiro_W = shapiro_result$statistic,
  Shapiro_p = shapiro_result$p.value,
  T_test_t = t_result$statistic,
  T_test_df = t_result$parameter,
  T_test_p = t_result$p.value,
  Wilcox_V = wilcox_result$statistic,
  Wilcox_p = wilcox_result$p.value,
  Cohens_d = cohen_d_result$estimate
)

write.csv(results, "Synchrony_vs_Pseudosynchrony_results.csv", row.names = FALSE+
```