Linkage and Observed Behavior for Visualizing Engagement (LOVE): Visualizing Physiologic Synchrony in Parent-Child Dyads of Typically Developing Children and Children with a Diagnosis of Autism

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Figure 1: Visualizing physiological synchrony application summary view.

ABSTRACT

Linkage and Observed Behavior for Visualizing Engagement (LOVE) is a project aimed at developing a data visualization tool for clinicians to communicate observed and sensor data on parent-child physiologic synchrony and observed behavioral interactions. This open-source system uses Plotly and Dash to visualize dyad interactions by integrating moment-level indicators, aggregate summaries, and video-based navigation. The system was designed for parent-child dyads which include typically developing children and children with a diagnosis of autism. The system provides a reusable design blueprint for visualizing dyadic physiologic linkage in applied contexts.

Index Terms: Linkage, Physiologic Synchrony, Visualization, Clinician-Patient Communication, Dyadic Interaction.

1 INTRODUCTION

Physiologic synchrony or linkage is an alignment of physiologic function in the autonomic nervous system between two or more people and has been correlated with observed positive and negative psychosocial interactions [1, 2, 3]. Physiologic synchrony has been correlated with observed parent-child attunement [1], couples' relationships [4], and therapy outcomes related to therapist and patient physiologic synchrony [5]. Although sensor data and statistical methodology have been leveraged to describe linkage [6, 7, 8, 9], there is a lack of data visualizations of physiologic linkage designed to communicate behavioral patterns and linkage events. Insights into behavioral patterns surrounding linkage events could be informative for clinicians, researchers, and mental health providers to communicate with patients and parents to develop a shared understanding of behaviors that may influence interactions. Children with a diagnosis of autism demonstrate features of varied social communication and interaction patterns [10]. Gaining insight into linkage and behavioral interactions may be benificial for parents of children with an autism diagnosis. Using Plotly [11] and Dash [12] we developed a data visualization dashboard to view key data points summarizing physiologic synchrony and behavioral data from structured dyad interactions.

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2 RELATED WORKS

There is a clear gap in patient-facing systems for visualizing physiologic synchrony and derived data attributes [13, 14, 15]. Prior work in three key areas informed the development of our data visualization dashboard including physiologic synchrony, visualizations for physiologic synchrony, and data visualization for patient and clinician communication.

2.1 Physiologic Synchrony

Physiologic synchrony is an emerging domain with expansion on sentinel works by Levenson and Gottman in 1983 identifying the notion of physiologic linkage in human relations [16]. Physiologic synchrony has been correlated with observed parent-child attunement [1], couples' relationships [4], and therapy outcomes related to therapist and patient physiologic synchrony [5].

With the advancement of sensor technology and accessibility, the measurement of synchrony is advancing. Physiologic synchrony has been measured using a variety of sensors and statistical methods [17, 7, 8]. Data types used to measure linkage include cardiac sensor data, electrodermal activity, electroencephalogram (EEG), and respiratory data [17, 9, 5]. As the field continues to expand, there is a clear opportunity for visualization systems that translate these signals into interpretable representations to inform research and clinical practice.

2.2 Visualizations in Physiologic Synchrony

A preliminary review of existing research on data visualization of physiologic synchrony found limited prior work, supporting the novelty of this work and opportunity for foundational contributions.

The DIMS Dashboard [13] demonstrates an interactive visual approach to time-aligned video and synchrony data from neural sensing. Small multiples of time-series for sensing data and wavelet coherence scalograms are linked via brushing and zooming to provide rapid previews synced to video feedback or an overview of the entire recording. The primary audience for these visuals is researchers studying social interaction [13] and the dashboard is tailored specifically to this use case. ELAN [14] is a long-standing electrophysiology toolbox for visualizing synchrony of local field potentials and electroencephalography data. This work is more generalized than DIMS and has been used in broader applications of research [14]; however, the target audience for the visuals is also scientists in physiology and other related fields.

Wavelet analysis graphs are popular within research communities for time-series data, and are frequently used to visualize recordings of physiologic synchrony [18, 19]. However, these visuals are very dense and require an understanding of the statistical analysis used to derive and encode the data. The properties of synchrony data call for specialized visual encodings to support interpretation from broader audiences outside of the scientific community; Li et al. [20] represent dyadic EEG similarities with moiré patterns [21] in virtual co-viewing environments. These allow for rapid assessment of the data due to the reduction in encodings and data density.

2.3 Clinician and Patient Communication with Visuals

The use of information visualization to communicate patient health data is well established and supported by extensive research [15]. There are three main communication styles in clinician-patient interactions: patient-centered communication, clinician-centered communication, and ”patient-centered communication with need orientation” [22]. Patient-centered communication is characterized by empathetic and socially responsive dialog when conveying health data and is typically the most successful style of communication for patient comprehension [22]. Need-oriented communication prioritizes the patient's personal and emotional needs; while it may be less effective for conveying complex health data, it can improve relationships and build trust between the patient and the physician [22]. It is important that information visualization for patient communication and comprehension also reflect these dynamics from non-visual modes of communication.

Turchioe et al. [15] found that line graphs and number lines are the most common graph types for patient-facing information visualization, typically for encoding raw and continuous data. The authors highlight that there is a substantial gap in patient-facing visualizations relative to physician-facing visualizations, and note a lack of consistent approaches for selecting and developing visualizations for a specific health dataset or task. They also observed limited analysis and data processing on the presented patient data, limiting patient insight into their health information [15].

3 Process

The initial process began with multiple discussions with domain experts to identify the problem and the best data to use to develop a prototype for visualization of physiologic synchrony. Current visualizations are limited and complicated to interpret. Visualizing the data for each dyadic encounter was discussed from the perspective of different stakeholders, including researchers, clinicians, and parents or patients/clients. Each category of stakeholder was involved in the initial discussion. The lack of a visualization tool to facilitate communication with parents about behaviors and physiologic synchrony after structured dyadic encounters was identified as the primary goal of our project.

Our process is detailed here including expert interviews, task analysis, data exploration, and an iterative visualization design process incorporating user feedback and usability testing.

3.1 Expert Interview

To better understand the applications and visualization needs for physiologic synchrony, we interviewed Anna Wallisch, PhD, OTR/L. Dr. Wallisch is an occupational therapist and Assistant Professor in the Division of Developmental and Behavioral Sciences in the Department of Pediatrics at the University of Kansas Medical Center. Dr. Wallisch is a researcher and clinician whose research is centered on eating behaviors among children with a diagnosis of autism. She is interested in physiologic synchrony between children and their parents and its impact on eating behaviors.

Verbal consent to participate in the interview was obtained. A semi-structured interview was conducted to learn more about physiologic linkage, the current use of physiologic synchrony data, and data visualization needs in Dr. Wallisch's role as a researcher and clinician. Typed notes were taken during the interview and were subsequently used for task analysis as described in section 3.3. The verbal consent verbiage, the interview guide, and interview notes are included in Appendix A.

3.2 Task Analysis

A task analysis was conducted following the expert interview to identify required functionalities and define success metrics for the visualization platform. Using Munzner's task analysis framework [23], interview notes, such as information on the background, needs, areas of improvement, and recurring phrases of the stakeholder, were coded into domain-specific tasks and assigned to abstract tasks (Appendix B). Tasks were classified in order of importance based on interview evidence (Table 1). In total, eight tasks were identified, predominantly low level abstract tasks, though high level and mid level tasks were also included. Tasks related to interpretation and interaction were ranked higher in importance due to their frequency and emphasis in the expert interview. The key takeaway was a clear gap in interpretable visuals that let parents and clinicians jointly analyze Parent Child interactions; thus, ”Analyze Parent Child Interactions” was ranked highest. “Auto-jump to points of interest” followed, as it directly supports that top-level task and addresses a noted pain point in current side-by-side data and video tools. Generating a summary was also deemed critical to give parents an understandable overview they can take home or use to track progress, connecting to bio-feedback for monitoring triggers and improvements (ranked last). Viewing linkage within the data and identifying leading/lagging participants were next as clinician “nice-to-haves”; raw magnitude values, however, were seen as less relevant for parents. Including leading/lagging behaviors helps integrate behavioral with sensor data. Finally, the ability to compare linkages by magnitude or duration was ranked as a useful, but non-essential, aid to summaries and interaction. Bio-feedback was mentioned briefly and retained due to its relation to the preceding tasks.

3.3 Data

Data from the enTRAIN study was used for this project [24]. The dataset includes physiological data and video recordings of structured interactions between dyads of children (n=30) and a caregiver or researcher during structured interactions or tasks [24]. Participants included typically developing children (n=22) and children with a diagnosis of Autism Spectrum Disorder (ASD) (n=8).

Each dyad (parent-child/researcher) has associated video, physiologic, and behavioral data. The physiologic data and video data are timestamped to allow for alignment. Physiological data includes electrodermal activity (EDA) and cardiac data for each member of the dyad. EDA was collected with a Q-Sensor. EDA for some participants was corrupted, therefore excluded from the larger dataset. Cardiac activity was recorded using Actiwave Cardio sensors. Behavioral coding of vocal behavior for vocal turn taking (ST/switching turns) and interrupting turns (IT/interrupting turns)

Table 1: Task Analysis, following the framework of Munzner [23]. Tasks are ordered from most to least important.

Task Key	Domain Task	Abstract Task	Task Level
Task 1	Analyze Parent Child Interactions	Consume (Discover)	High Level
Task 2	Support jumping to points of interest in video	Locate	Mid Level
Task 3	Generate Summary of the Data	Summarize	Low Level
Task 4	View linkage magnitude within data	Compare	Low Level
Task 5	View leading and lagging participant within linkages	Locate and Identify	Low Level
Task 6	Compare linkage attributes	Identify and Compare	Low Level
Task 7	Correlate video behaviors with physiologic data	Produce (Annotate)	High Level
Task 8	Provide bio-feedback for tracking triggers and progress	Consume (Present)	High Level

was indicated with 1 = occurring and 2 = not occurring for each of the metrics. Additional behavioral coding includes supported joint engagement (`SJE`), coordinated joint engagement (`CJE`), and any joint engagement (`JE`) between the dyad. The engagement metrics were also coded as 1 = occurring and 2 = not occurring. Vocal turntaking was manually coded by the research team.

Video data was recorded using a GoPro. The sampling rate of the video data is 60 Hz and the sampling rate for the sensor data is at 1 Hz. This represents 60 data points/frames for the video for every 1 data point of the physiologic data. The dataset included raw data and processed data. Pre-processed cardiac synchrony data was calculated using Morlet wavelet analysis [25]. Given the corruption of some of the EDA data, cardiac data was used as the primary physiologic synchrony measure. Proximity was calculated using Ultralytics Yolo version 11 [26] for object detection and MiDaS [27] for depth detection. The resulting metric is scaled so that higher values correspond to greater distances between participants.

The three physiologic measurements used for our visual include low-frequency coherence (`lf coh`), high-frequency coherence (`hf coh`), and interbeat interval (`IBI`) for parent and child. Low-frequency coherence is defined as the alignment of slower moving signal fluctuations. High-frequency coherence is defined as the alignment in rapid, moment-to-moment signal fluctuations [17]. Interbeat interval `IBI` is a measure of the time between heart beats and is reflective of heart rate variability (`HRV`) and the activity of the sympathetic and parasympathetic nervous system [28]. Normalized `IBI` values were averaged within non-overlapping 1-s bins to align with the coherence sampling frequency.

From the original dataset we computed (i) coherence episode durations (consecutive samples with coherence ≥ 0.5), (ii) counts of synchronized episodes, (iii) counts of joint-engagement episodes (a value of 1 in either `SJE` or `CJE`), and (iv) joint-engagement durations. All metrics were generated using reproducible Excel formulas.

Exploratory plots and linear models (Appendix D) indicate that proximity is positively related to coherence: `lf coh` increases with greater separation between participants ($p < 0.0001$), and a weaker but significant effect is present for high-frequency coherence (`hf coh`; $p = 0.0028$). Across the recordings, `hf coh` values were more numerous than `lf coh` values, and `hf coh` displayed greater within-series variability. We found no significant linear associations between coherence values and either parent or child `IBI`.

Based on expert interview, task analysis, and feedback from domain experts, the visualization focused on coherence data and behavioral data.

3.4 Usability Testing

We conducted usability testing in the classroom setting and during an office hours session with a total of 4 participants. We used open-ended exploration and task-directed usability. Given the specific nature of our synchrony data, we introduced participants to the general topic of physiologic synchrony, the dataset, and our goal for the visualization. We then asked participants to explore the visual and share what they were experiencing and any thoughts by narrating their thoughts as they explored the dashboard.
We then asked participants to complete the following tasks.

- Task 1: Find what the parent and child are doing at the maximum point of synchrony.
- Task 2: Describe the summary of coherence and engagement at 10:52 am.
- Task 3: Who is leading the most during physiologic synchrony?

Each session lasted ten minutes. We did not interrupt the user to begin the tasks if they were sharing feedback out-loud. Some participants did not have the opportunity to attempt all tasks. We took notes during the session and subsequently identified themes from the usability testing session.

Thematic analysis of the notes was conducted and three general categories for improvement emerged including (1) overall visualization aesthetics, (2) navigation and interactivity, and (3) labeling of the data. Each category of feedback is summarized below.

(1) Overall visualization aesthetics themes.

- Participants reported the summary page was “information intense.”
- The colors were not distinct enough for each of the categories, there was too much green and blue.
- It was confusing to have the high- and low-frequency synchrony with the same color scales.
- Participants liked the cohesion of the colors throughout.

(2) Navigation and interactivity themes.

- Visual interactivity features were not evident to participants.
- Navigating between the video and the summary page was not streamlined. Suggestion of only one page with the video on that page.
- Interactivity was not evident. Suggestions include improved labeling, gif of interactive features that appear when the participant hovers in the area. Show more tooltip cues.
- Participants were heavily focused on the heat maps, with less time and attention on the glyph and point-in-time data. The value or use of the point-in-time data and the glyph was not clear on the summary page.
- The relationship between the glyph and the heatmap was not obvious.

- Confusion about interactions related to the heat map navigation with the video. The indicator line on the heat maps was not navigated as expected, participants expected the heatmap indicator line to navigate the video. Time on the video was play time, and the heatmap timeline was time of day. The location of the video navigation did not align with the heat map indicator bar.
- Filtering data by time points of synchrony would be interesting to see patterns of high points in one visual to look for patterns.

(3) Data labeling themes.

- Confusion about the heatmap on the video view and what each row means. Each row could use a label on the video page.
- The hover feature was helpful; one participant suggested using hover to show data at that time point for synchrony, leading behavior, and engagement.
- Font size was small and difficult to read in some areas.
- Font was not consistent throughout the visualization.
- Legend titles were not clear, and the words were too small.
- Dyad behavior labeling was not clear, and the words were too small.
- Dyad behavior cards had too many words, suggestion for adding a 3 icons with 3 colors, put a bold stroke of color.
- It was not clear what the possibilities for dyad behavior were, suggestion to add an array of the 3 icons.
- Avoid abbreviations or have a legend near the pie chart.

The results of the usability testing were considered in the iterative design process. Details are discuss in section 3.5 Design Iterations and Sketches.

3.5 Design Iterations and Sketches

Throughout the development of our physiologic synchrony dashboard, we followed an iterative design process informed by early sketching, prototyping, and multiple rounds of informal usability feedback. The sequence of sketches and preliminary mock-ups (Figures 2- 8) reflects the evolution of our design, understanding of stakeholder needs, and how best to depict that information through visual encodings and interactions.

Following our expert interview and task analysis, our earliest hand-drawn sketches focused on establishing the primary views of the system: a high-level summary of the dyadic encounter and a time-synchronized video view. These initial drawings explored a variety of representations for synchrony and behavioral data, including the use of glyphs (Figure 3), heatmaps (Figure 2), scatter plots (Figure 3), and simple graphics such as bar and line charts (Figure 2). From these initial sketches, we moved forward with our idea for a dual dashboard layout and highlighted the glyph, heatmaps, bar chart, and scatter plot as effective components to incorporate. Following the recommendations of the project's advisors, we used sports-based visualizations for inspiration, and the first iteration of the synchrony glyph (Figure 3) drew on visualization techniques from tennis performance dashboard, which used segmented circular forms to communicate player performance and temporal balance [29].

After we translated the sketches into preliminary prototypes (Figures 5 and 6), stakeholders raised concerns about the interface, specifically about the excessive use of bar charts, color pallette, and visuals that were not relevant to patients. These critiques prompted us to re-evaluate our chosen set of visual encodings and replace elements with visuals that aligned better with our tasks and patient needs. A violin plot showing the distribution of time spent at various synchrony magnitudes was added in black of the scatter plot, visuals for raw heart rate variability data were removed, and a secondary bar chart for behavioral data was reworked to a pie chart (Figure 7). Additional heatmaps for behavioral data were included to further support Tasks 5 and 7. With the feedback from usability testing and advisors, minor adjustments were made to the color pallette, legend, and pie chart (Figure 8) before usability testing.

Live user feedback indicated that new users felt overwhelmed by the presence of Point-In-Time visuals on the Home Summary view during onboarding. In response, these visuals were removed from the default layout and made accessible through a Point-In-Time toggle. Testers also reported difficulty identifying which components were interactive and what information each chart encoded, prompting the addition of tooltips. This sequence of refinements ultimately shaped the final version of our visualization system.

4 Design

This section describes the visual encodings and interactive elements incorporated into our final dashboard and explains how these choices address the tasks identified in our task analysis. Early exploratory sketches and iterative stakeholder feedback informed the selection of each component.

4.1 Home Summary View

To support the high-level task of Generating a Summary of the Data (Task 3) and Analyzing Parent Child Interactions (Task 1), the home summary page Figure 1 contains a selection of components displaying aggregated or high-level data. Within each visual component, a tooltip allows users to learn more about the chart and its potential

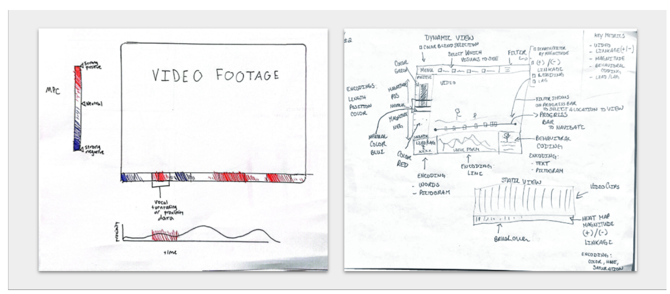

Figure 2: Independent sketches generated after expert interview and task analysis. Both visuals incorporate a dashboard where video playback is synchronized to a heatmap.

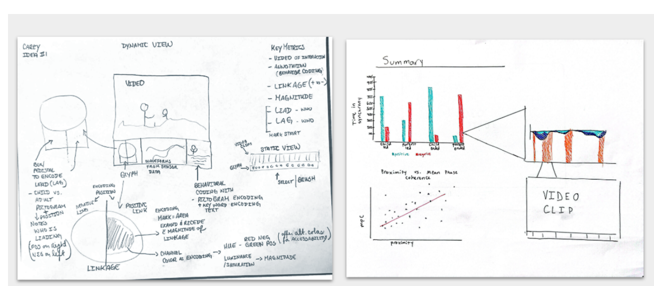

Figure 3: Independent sketches generated after expert interview and task analysis. Key takeaways from these designs are the need for a glyph or compact visualization for synchrony values within the video view and a summary page showing derived metrics.

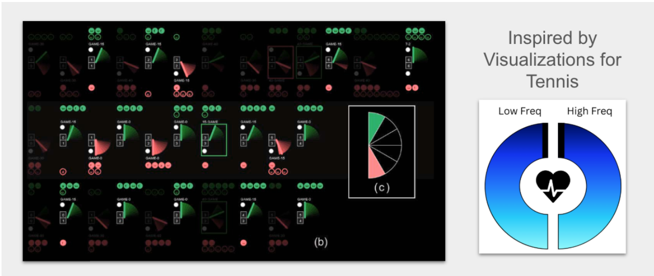

Figure 4: Inspiration for the synchrony magnitude glyph was drawn from the work of Polk, J. Yang, Y. Hu, and Y. Zhao in tennis match visualization [29]. The authors' use of segmented radial forms, which encode performance through position and color, aligned with our goal of presenting moment-level synchrony in a compact and easily interpretable fashion.

Figure 5: The original design of the Summary Home view, featuring the synchrony glyph, a visual for heart rate, dyad interactions, the leading behaviors bar chart, a scatter plot showing the relationship between distance and synchrony, the summary table, a bar chart for leading participants in joint engagement, and the heatmap. Ultimately, the visuals for leaders in joint engagement, heart rate, and distance versus synchrony were reworked due to irrelevance and design quality.

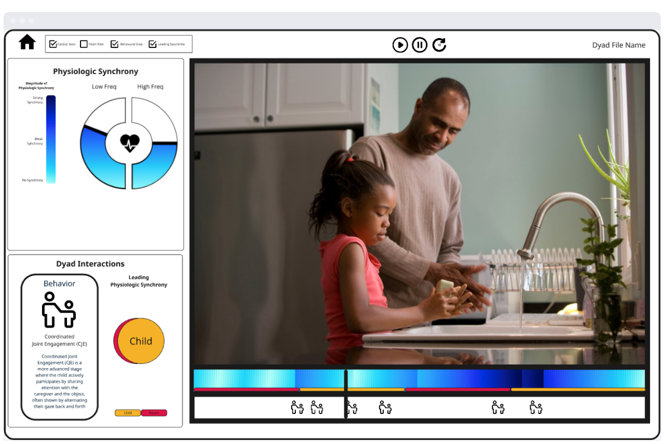

Figure 6: The original design of the Video Play view, which remained similar to the final design iterations.

interactive features. A bar chart conveys how often each interaction partner initiated a high- or low-frequency synchronous moment, which was defined as a consecutive period of synchrony magnitude ≥ 0.5. Length was chosen as the primary encoding because it supports rapid magnitude comparison. Color encodes participant identity (parent vs. child) using a palette consistent with the rest of the interface, helping users recognize which member of the dyad is being referenced.

Selecting a bar filters the subsequent violin plot for synchrony magnitudes and donut chart for joint engagement to display only the data involving the chosen leader. This interaction enables focused examination of individual behavior patterns (Task 5) and supports analysis of trends between the behavioral data and physiologic data (Task 7). Clicking again clears the filter and returns the view to its aggregate form.

We represent the distribution of synchrony measurements using a violin plot, which highlights the density of values across the synchrony spectrum. The width of the violin plot is used to encode the number of synchrony recordings, and height is used to index the synchrony magnitude. This encoding communicates where the dyad spent most of their interaction time and how often they crossed the threshold of 'meaningful' or significant synchrony, which is marked explicitly on the plot. These characteristics support comparisons of synchronous recordings within a session (Task 4) and across multiple sessions depending on data availability (Task 8).

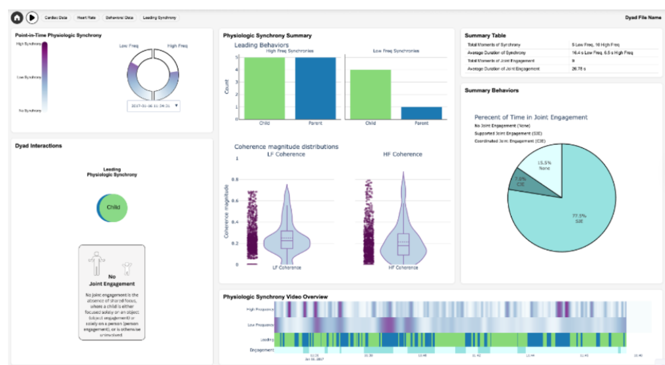

Figure 7: The second iteration of the Summary Home view design. The new layout features a pie chart for percentage of time spent in joint engagement, a modified color scheme, additional heatmaps, a violin plot for synchrony magnitudes, and the removal of heart rate visuals.

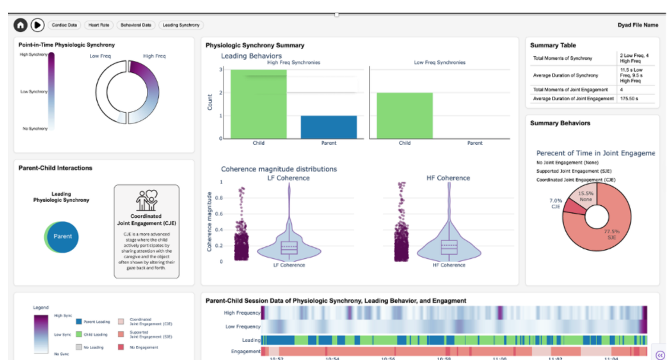

Figure 8: The third iteration of the Summary Home view design, including the final color pallette, a legend, and a donut chart to replace the previous pie chart for visual consistency with the Point-In-Time glyph.

Colors from Plotly's BuPu colorscale were chosen to align visually with the synchrony heatmaps while maintaining distinction from other visualizations.

A summary table provides high-level metrics relevant to the overall session, addressing Task 3. Because the purpose here is not to compare values but to allow users to extract clearly defined quantities, a tabular form is the most direct and efficient encoding.

Below the table, a donut chart shows the time spent in each engagement state (coordinated joint engagement, supported joint engagement, or no engagement). This representation communicates the relative prevalence of behaviors in a way that is immediately interpretable. Arc length communicates proportion, and text labels reinforce exact values to avoid common misreading issues associated with pie-like charts. The discrete color pallette parallels that of the behavioral heatmap, with the lowest-intensity hue assigned to "no engagement" to match clinician expectations. These elements support tasks related to understanding behavioral patterns (Task 7) and retrieving key high-level metrics for takeaway or comparing results between sessions (Tasks 3 and 8).

Users may optionally activate a Point-In-Time mode, which reveals second-level information synchronized with the time-aligned heatmaps. When enabled, the view initially aligns with the first second of the dataset and updates dynamically as the user moves the central cursor through the heatmaps. A custom radial glyph represents moment-level synchrony. Its shape and color encode the magnitude of the synchrony value to support rapid interpretation in peripheral vision. A gradient ranging from light blue to deep purple communicates the increasing synchrony strength in a manner that complements the aggregate heatmap. The accompanying behavioral cards provide categorical context at the same time stamp, creating a unified snapshot of the data from moment to moment to support Tasks 2, 4, and 5. These visuals were deliberately removed from the primary Home Summary view due to user feedback on an overwhelming amount of visualizations to onboard.

The bottom heatmaps provide a basis for temporal exploration of the data. Each vertical slice represents one second of the recorded interaction. The upper heatmaps encode synchrony data using a sequential color gradient to represent high- and low-frequency synchrony values, while the lower heatmaps employ a categorical pallette to encode behavioral states. This combination allows users to observe how quantitative synchrony patterns intersect with categorical behavioral patterns (Tasks 4, 5, and 7). Clicking on the heatmap activates a 60-second analysis window, highlighted with a yellow frame. The window filters the violin plot and the engagement donut chart to display only the data contained in the selected interval, giving users the capability to inspect specific periods of interest and correlate related data attributes (Tasks 2 and 6). If Point-In-Time mode is active, the cursor position also updates the synchrony glyph and behavioral cards (Figure 9).

4.2 Video Play View

The Play View implements the recorded session video with the Point-In-Time visuals and heatmaps. As the video progresses, the timestamp drives the cursor position in the heatmaps and updates the associated glyph and behavioral cards (Figure 10). The user can also navigate to points of interest within the data using the video playback navigation (Task 2). This alignment enables users to directly relate behavioral and synchrony indicators to the corresponding raw video footage, helping them contextualize quantitative signals within the actual interaction (Task 7).

4.3 Implementation

All components were implemented using Plotly [11] and Dash [12], with Dash-Player enabling synchrony between video playback and the time-based charts. This architecture supports the linked brushing, cross-filtering, and real-time updates used throughout both views through a series of Dash callbacks. The system exhibits initial steps towards modularization for applications on similar datasets through a data configuration script, and each visual can be modified within its respective component file for customization to other use cases.

The backend logic parses quantitative and categorical data streams, including low-frequency coherence, high-frequency coherence, engagement encoding, and leading participant encoding, into a unified time index. This pre-processing step establishes a one-second sampling grid for consistent alignment across visuals and video playback. Additional derived metrics, such as synchronized-episode durations, counts, and behavioral engagement windows, are computed on initialization of the dashboard.

The front-end visualization layer is composed entirely of Plotly figures, chosen for their ability to support updates through Dash callbacks and alignment with course materials. Dash's state model was used to facilitate interactions for brushing and filtering, allowing each component to publish events to the shared callback graph.

The Play Video view uses Dash-Player to synchronize the video playback head with the heatmaps and Point-In-Time visuals. As the video progresses, Dash-Player emits timestamps at one-second intervals that feed directly into update callbacks for the Point-In-Time visuals and cursor over the heatmaps. This creates a tightly coupled moment-to-moment display of physiologic synchrony and behavioral states. The use of Dash-Player also supports scrubbing and pausing while maintaining synchronization with all visual encodings.

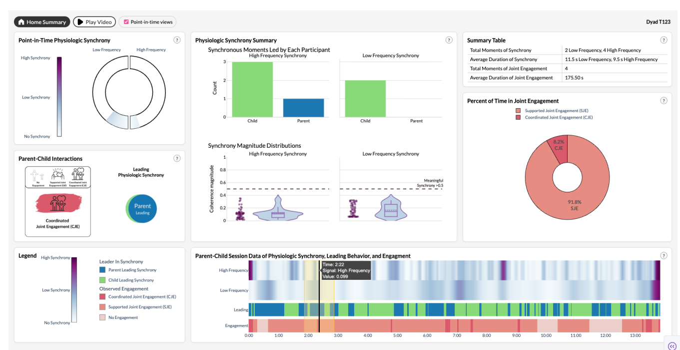

Figure 9: The application Home Summary view with brushing and Point-In-Time mode activated.

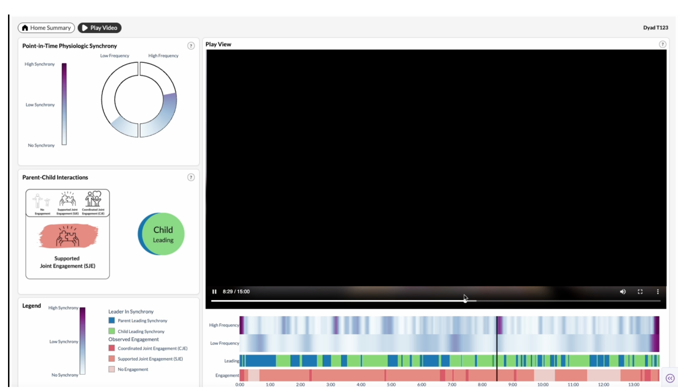

Figure 10: The application Video Play view with video navigation to update the heatmap cursor (bottom) and Point-In-Time visuals (left).

4.4 Color Palette

Careful consideration was given to color encodings throughout the visualization design process with priority on discrimination and then aesthetic appeal. The visualization conveys three categories of information about the dyadic iterations including physiologic synchrony, behavioral engagement, and leading behaviors. During initial renderings of the heat map design in Plotly [11], several color palates were trialed and the blue-purple (BuPu) color palette was effective at showing the varying levels of synchrony on the heatmap with clear distinction of magnitude. See the blue-purple heatmap in the color evaluation process represented in Figure 11. We then used the Colorgorical web-based tool [30] to identify a color pallette. We used the dark purple in the Plotly blue-purple color scale as a foundational color and selected high levels of discriminability and preference to identify colors for the leading and engagement behavioral encodings. We identified color suggestions we preferred and ruled out colors that were too close to purple in color to avoid confusion in color encodings between the categories of data(Figure 11). We determined the blue and green colors would be a distinct encoding for the parent and child leading behavior. We initially selected colors in the cyan family as the encodings for the engagement behaviors.

During the usability studies and through feedback from advisors, it was determined that cyan was not distinct enough from the leading behavior encodings and a new color palate was investigated. Colorgoical was used to identify a coral color palette by adding the purple, green, and blue colors and searching. The coral color denoted by the arrow in 11 was identified, then used to find colors with a clear hierarchy to represent the increasing levels of engagement behaviors. The final color palette offered distinction among and within the categories of data. Physiologic synchrony is Plotly's blue-purple color scale, leading behaviors are dark blue for the parent and light green for the child, and engagement behaviors are in the coral family (13).

5 Discussion

The development of our physiologic synchrony dashboard reveals several broader implications for the interpretation, communication, and practical use of synchrony data in clinical and patient-facing settings. Our work demonstrates how heterogeneous dyadic data, consisting of physiological measurements, behavioral codings, and video footage, can be integrated into a unified analytic environment that supports both expert reasoning and client-facing interpretation. The resulting system highlights challenges in designing systems for multiple stakeholder groups and illustrates strategies to balance representational richness with cognitive accessibility in a healthcare setting.

Figure 11: The color selection process Colorgorical [30]. This is the final version of the summary page in the monochromatic view to validate the discernibility of the colors in black and white.

Our findings highlight the importance of interactive design when working with multifaceted synchrony data. Brushing and linking across heatmaps, summary plots, and video provided a consistent mechanism for locating and contextualizing synchrony events, which clinicians noted is difficult in their current workflow of moving among disjoint tools for physiology, behavioral, and video data. While our dashboard does not eliminate these broader workflow challenges, consolidating these data streams into one environment helps reduce some of the effort involved in connecting physiological patterns with corresponding behavior and video moments. Usability testing also informed several changes aimed at managing cognitive load, including relocating the Point-In-Time visuals behind a toggle and adding tooltips ad legends to clarify interactive elements and chart encodings. These adjustments supported a more approachable on-boarding experience while preserving access to detailed, moment-to-moment information when needed.

More broadly, the system addresses a gap identified by domain experts regarding the lack of accessible tools to communicate physiologic synchrony to parents and caregivers. Existing research visualizations, such as wavelet coherence plots, are statistically expressive but not interpretable by non-specialists. In contrast, our

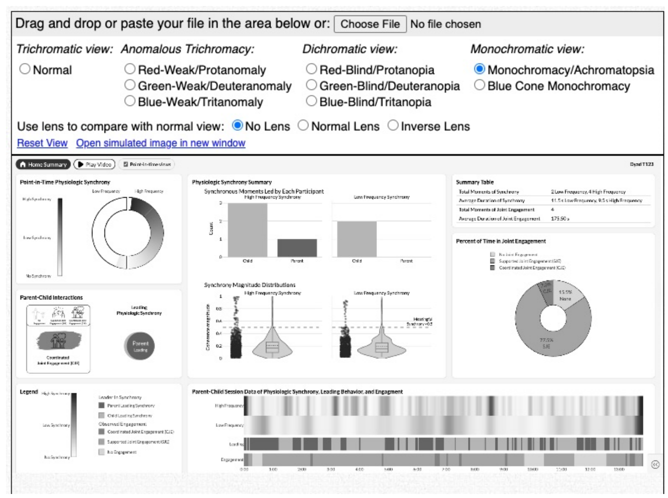

Figure 12: The color selection was validated for users with color visual impairment using the Coblis - Color Blindness Simulator [31]. This is the final version of the summary page in the monochromatic view to validate the discernibility of the colors in black and white.

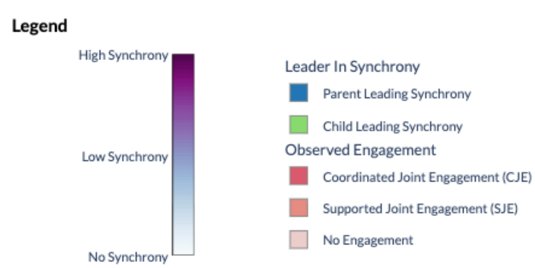

Figure 13: The color pallette for the visualization is represented in the legend with distinct color encoding for each data category. Physiologic synchrony is Plotly's blue-purple color scale, leading behaviors are dark blue for the parent and light green for the child, and engagement behaviors are in the coral family.

use of categorical behavioral encodings, violin plots for distributional reasoning, and a glyph-based representation inspired by prior sports visualization work aligns with best practices in designing for mixed-expertise audiences. These representations support high-level questions about the presence, strength, and behavioral context of synchrony without requiring statistical literacy, thus facilitating clinician-patient dialog during feedback sessions.

Although the dashboard demonstrates the potential of visualization to convey complex interpersonal physiologic insights, several limitations remain. First, the system currently depends on preprocessed synchrony and behavioral data; real-time computation and streaming are outside of the present scope. Second, although our usability testing revealed clear concerns about cognitive load, a more extensive evaluation with a broader sample will be necessary to assess how well these design choices generalize. Finally, as the dashboard is intended for open-source use, future work will focus on adapting the codebase to support greater customization, enabling users to tailor chart types, encodings, and layouts to different synchrony-related datasets. Extending existing features within the Play Video view with additional interaction, such as allowing users to navigate the heatmap cursor directly rather than relying solely on Dash-Player's video playback features, can further address issues encountered in usability testing. Future iterations of the project may also incorporate additional physiologic datasets, including electrodermal activity, to test the applicability of the dashboard across varying scopes of synchrony analysis.

Despite these limitations, our system contributes a reusable design blueprint to visualize dyadic physiologic linkage in applied contexts. The integration of moment-level indicators, aggregate summaries, and video-based navigation illustrates that multi-level data can be coherently expressed in one framework. Furthermore, the design lessons derived from our iteration cycles provide guidance for future systems at the intersection of physiologic and behavioral studies and human-computer interaction. The dashboard demonstrates that, with appropriate encodings and interactions, physiologic synchrony can be transformed from an abstract scientific construct into a comprehensible resource for clinical insight and patient engagement.

6 Conclusion

This work presented a visualization dashboard designed to help clinicians and caregivers interpret physiologic synchrony in parent-child dyads by integrating behavioral data, physiologic measurements, and video into a single analytical environment. Through iterative design and feedback from domain experts and stakeholders, we developed a set of visual representations that aim to make synchrony patterns more interpretable for mixed-expertise audiences. Visualization of physiologic synchrony has potential applicability beyond caregiver-child contexts, including understanding dyadic dynamics in couples, assessing social engagement among individuals diagnosed with autism, and supporting other areas where interpersonal coordination is clinically relevant. Furthermore, this work can aid clinician-patient communication by translating complex medical data into formats that are easier to discuss, interpret, and act upon for non-expert users. Future work will focus on applications of the tool on additional datasets, making the codebase more extendable, and supporting chart and glyph customizations.

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Appendices

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Appendix A: Interview Process

A semi-structured interview was conducted with an expert in the field. We interviewed a researcher and clinician (occupational therapist, OT) who conducts research involving eating behaviors among children with a diagnosis of autism with an interest in physiologic linkage and how parent-child linkage can influence eating behaviors. The interview went well and was informative. The expert in the field was able to provide information from the perspective of a researcher and as a clinician who interacts with patients and their families.

Through the interview process, we learned more about physiologic synchrony and possible applications. We learned that more had been done by the research team and lab in creating a preliminary data visualization tool with a focus on research needs. The need for both a researcher and the impact that this tool could have on clinician and family communication became evident during the interview and task analysis. With better communication tools about physiologic synchrony, clinicians could provide feedback on parent and child behaviors that may lead to synchrony, thus potentially influencing children's eating behaviors. This shifted our focus to addressing the needs of a different stakeholder, specifically the clinician, with a goal of improving interoperability and communication with the parent/patient.

Before the interview we developed an interview guide based on a preliminary discussion with experts in the field and review of the current literature. We took notes on a copy of our interview guide. The interview guide and our notes from the interview are included below.

Interview Guide

Participation Consent Verbal Consent

Thank you for participating in today's interview. The goal of the interview is to help us understand more about physiologic linkage, your background as a stakeholder related to physiologic linkage, and how you would use physiologic linkage information.

Our goal is to conduct a task analysis to design and build an interface that will be most useful to you and others interested in using physiologic linkage data.

We are looking to gather information about your experience; there are no right or wrong answers. Your responses will be used for a task analysis for our class, and we may use select anonymized quotes and the results of our task analysis in publications.

Your participation is voluntary, and if you would like to withdraw at any time, please let us know. Do you have any questions?

Participant Role Identification/Background

Note: Identify stakeholder role (researcher, therapist, parent)

- Could you describe your role and interest related to physiologic linkage?
    - Anna works at KU Medical center and is an assistant professor at the department of pediatrics. Her research centers around child autism and eating behaviors. In this domain, she is interested in physiologic linkage, including how parents influence eating
    - She is primarily a researcher
    - She also has contributed to pediatric tube weening studies in children with autism
    - Part of her role includes behavioral health coaching for how parents respond to child behaviors
        - Parents become in sync with their children's eating behaviors over time
    - She has a background in occupational therapy

Researcher Related Questions

- What is your educational background and experience?
- Could you provide us with a brief overview of your current research?
- Who are your primary research populations?
    a. Children (autism and non-autism), parents
    b.
- What are the primary goals of your research?
    a. Record mealtimes and play time in autistic and non-autistic groups, and record children's interactions with their parents during these times
    b. She is also interested in pain responses and pediatric chronic pain. The way that parents react to children experiencing pain can influence a child's behaviors and pain response. She

would like to apply this to gastro-intestinal pain since this is more prevalent in children with autism.

c. Wanting to apply it where there is higher parent-child stress and wanting to apply it to parent stress

Current Methods and Tasks

- Can you walk us through your current workflow of analyzing physiologic datasets?
  a. Step zero: Before recording, ensure ALL of the times are synced. Line up when parent/child started recording and when the video started.
    i. Primarily uses electrodermal sensors
    ii. Also interested in pulse rate variability, BVP
  b. Step One: clean the data and make sure it's valid. Look for values that are outside of range of what's possible, potentially from loose equipment.
  c. They code parent affect, child affect and how connected the 2 were
    i. They also code dyadic interaction nomenclature of eating: intervals for eating and sips, coercion and commands by parents, and child behaviors (how much talking, how many times the child leaves)
    ii. These codings are done with a program that is point-click (some are frequency counts or binary) in a python Shiny app
  d. Then, they have a couple of different visualizations they generate and assess
  e. They are working on adding an overlay to the video footage to see physiology while the participant is having the behavior (so you don't have to go between behavior and physiology visualizations)
    i. They have a graph that pops up to show cleaned electrodermal activity on top of the video at the upper left corner, but they want to be able to drag it around
    ii. They want more rich information from 1 viewing
      1. Add on some linkage variables (what is the indicator, who is leading it)
      2. When was the highest and lowest magnitude of linkage
      3. Summary statistics: who led majority of time for positive/negative linkage
- How do you interact with the data? Do you primarily look at the raw data or derived values/attributes?
- When analyzing this data, what are the most important features or attributes you expect to find?
- How do you find these attributes or statistics currently?
- How quickly do you need to derive these features and attributes? Within a few seconds? Minutes? Hours?
  a. Right now, all of the processes are separate which takes a lot of time.
- Are these datapoints or features shared with anyone else? Who?
  a. Nothing is shared right now but parents are interested
  b. PCIT clinicians are also interested in this for showing parents
  c. Currently, viz and data are primarily distributed for research purposes

Existing Gaps

- What existing tools do you use for conducting this data analysis?
  a. They use R and 3 separate python Shiny apps: video overlay, with EDA data, data cleaning, and point click program

    b. Right now, all these processes are separate,
        i. Cleaning the data
        ii. Extracted the data
        iii. Coding behaviors
        iv. Put into Video overlay is separate, although
        v. Wavelet analysis (in R for charts and extract linkage variables) shows some of invalid data
    c. Current TOOLS: R, Python overlay, MatLab, embrace plus sensors (Avaro to CSV) we have a python code to that, graphs the valid and invalid data, Shiny app program through Python
    d. Shiny Python (point click for behavioral analysis)
    e. Shiny app for Avero to CSV, and Validation of data points
- These tasks are separate
- Have you ever used Yuna's tool before? In what capacity?
    a. If yes:
        i. What are some of the limitations you have experienced using it?
        ii. What are some things that you really like about it?
    b. If no:
        i. What did you think of the demo? What are some aspects that you really liked about it?
            1. Value being able to have so many variables in 1 place (behavioral, linkage, physiology),
            2. Like the fact that you can toggle on and off what fields you saw
            3. Point and click to certain video features
        ii. Did anything jump out at you as being a potential pain point for usage? Such as readability, a feature was missing, feature?
            1. Data visuals are separate from the video
            2. They want to be able to easily jump to points of interest (high magnitude synchrony) without scrolling through all of the footage to try and compare
        i. The current Shiny app for overlay EDA:
            3. Value the overlay on the video
            4. They want to be able to move graph around and resize
            5. It only shows EDA but doesn't show physiologic indicators or behavioral coding
            6. They don't want it to be too messy with too much data

Goals

- Why do you want to visualize this data?
    a. To make interpretation easier. A lot of linkage analyses visuals are not easily interpreted like the wavelit and lattice charts. The charts look cool but take a while to interpret.
        i. Interpretation is a major theme here
    b. Wavelet and lattice – the charts look cool but are hard to interpret
- What kinds of analysis do you hope to support with the inclusion of visuals?
    a. Linkage analyses, visually inspect what is happening with physiologic data and sync with the camera
    b. It's a nice visual validation of what is happening in the data

- Please rank the following objectives in order of most important to least important:
    - quicker/automated analysis
    - identify new trends or attributes that could not be recognized without visuals
    - succinctly present results to external stakeholders
        - Highest priority: present to external stakeholders because it could become a tool for progress response and bio feedback. No current tools to support “This is what’s happening, this is what we can improve, this is what we can keep doing” for parents
        - i. Second highest priority: Quicker and automated analysis
- In an ideal scenario with unlimited funding and unlimited access to software developers, what would this tool look like to you?
    a. What could it provide that you currently do not have?
        i. All-in-one process on one platform
            a. They want more ways to visualize the data. There is a particular interest in charts more applicable for both research and clinicians. They also want easy visuals for parents in terms of video bio-feedback. It is extremely important for parents to see instances and areas of improvement and areas of strong interactions.
    b. What do you currently have or do that it could improve upon?

Overall Reflection

- If there was one thing you could change to make your life easier, what would it be?
    - All-in-one platform for visuals and quality checking for other physiologic data
    - Make python program adaptable for multiple sensor types.
- Tools? Workflow?

What additional information would you like to share with us?

She is going to show Yuna’s program

CAREY’s NOTES

Participant Role Identification/Background

Note: Identify stakeholder role (researcher, therapist, parent)

- Could you describe your role and interest related to physiologic linkage?

NOTES:

I am at KU medical center and a clinicl professor

Eating behaviors

10% in the interdisciplinary feeding clinicic, we know that there are a lot of parent behaviors that can support eating behaviors

Bidirectional impact

You can feel the tension, and then you can feel this cycle

Another side, I helped with pediatric tube feeding studies

G or GJ tubes

Parents becoming

Clinical background;

I remember

Researcher Related Questions

- What is your educational background and experience?
- Could you provide us with a brief overview of your current research?
- Who are your primary research populations?
- What are the primary goals of your research?

NOTES:

Wanting to apply it where there is higher parent-child stress

And wanting to apply it to parent stress

Pediatric chronic pain, we see the way the parents react to a painful procedure can influence how the child reacts later.

Related to vaccines

Pain dismissal in the field of pediatrics

I would love to apply it to gastrointestinal pain because there is a higher rate in that.

Some of the indicators that

Current Methods and Tasks

- Can you walk us through your current workflow of analyzing physiologic datasets?
- How do you interact with the data? Do you primarily look at the raw data or derived values/attributes?
- When analyzing this data, what are the most important features or attributes you expect to find?
- How do you find these attributes or statistics currently?
- How quickly do you need to derive these features and attributes? Within a few seconds? Minutes? Hours?
- Are these data points or features shared with anyone else? Who?

NOTES:

Visualization is a huge piece of physiologic linkage, and I am just learning as well.

First, we are cleaning the data and syncing the time

We use Apple Time, and we make sure that the time link,

We are looking at a an overlay of the data on a visual

We do behavioral coding as well

Primarily working with electrodermal, but I am becoming interested in the pulse rate variability and blood volume pressure

OVERLAY of the data on a video

Currently, there is a graph that will pop up in Python code

Other research assistants are able to process the data

It could be improved to get more information

The indicator is that there is a linkage, who is leading, who is lagging

Is there an easy way to look at the highest magnitude and the lowest magnitude or highest and lowest linkage

What is happing at really high and low points

Summary statistics could be interesting, who lead

Pulls clean EDA and transposes on the video, it goes to the upper left and you can’t move it

Sometimes you can’t see the axis, kids in the play seen

Being able to see highest levels

I like how Yuna's is too,

Positive to negative child affect

Dyadic Interaction Nomenclature of eating

Codes for bites, sips, when a parent gives a command , what is it, it's not a command it's a coercion, how much the parent or child is talking

Helpful to go to those areas where we see more bites

Behavioral coding, we have it so, it is a program that is a point click and exports into a redcap form, some are frequency, some are count

Being able to see it together would be helpful. Right now I have to go back and forth

For these different attributes that occur

Right now, all these processes are separate,

- Cleaning the data
- Extracted the data
- Coding behaviors
- Put into Video overlay is separate, although
- Wavelet analysis (in R for charts and extract linkage variables) shows some of invalid data

Current TOOLS: R, Python overlay, MatLab, embrace plus sensors (Avaro to CSV) we have a python code to that, graphs the valid and invalid data, Shiny app program through Python

Shiny Python (point click for behavioral analysis)

Shiny app Avero to CSV, and Validation of data points

These tasks are separate

Tried it a few different ways

They are not currently shared, but I have had a lot of parents who have been interested in seeing it.

Primarily distributed for research purposed

Clinicials that do parent-child interaction therapy, they do behavioral coding as well

It is very based on parent-child behavior

Existing Gaps

- What existing tools do you use for conducting this data analysis?
- Have you ever used Yuna's tool before? In what capacity?
    a. If yes:
        i. What are some of the limitations you have experienced using it?
        ii. What are some things that you really like about it?
    b. If no:
        i. What did you think of the demo? What are some aspects that you really liked about it?
        ii. Did anything jump out at you as being a potential pain point for usage? Such as readability, a feature was missing, feature?

NOTES:

The tool Yuna developed

POSITIVES:

Being able to have so many variables in one place,

Toggle on and off was helpful

Point and click to certain points in the video easily

AREAS FOR IMPROVEMENT

Video overlaying the data

Things to add on would be able to easily go to points of more interest, this is a point were there is really big synchrony

HUSBANDS TOOL

Positive

Overalay

Negative

Need to be able to move the graph, it obstructs the faces and things we want to see

Toggle would be good

Physiologic indicators

Add behavioral coding

It could be too messy too

Anna - will share the GitHub site and video with us

Goals

- Why do you want to visualize this data?
- What kinds of analysis do you hope to support with the inclusion of visuals?
- Please rank the following objectives in order of most important to least important:
    - quicker/automated analysis
    - identify new trends or attributes that could not be recognized without visuals
    - succinctly present results to external stakeholders
- In an ideal scenario with unlimited funding and unlimited access to software developers, what would this tool look like to you?
    a. What could it provide that you currently do not have?
    b. What do you currently have or do that it could improve upon?

NOTES:

It makes interpretation easier

Linkage has these visuals that

Wavelet and lattice – the charts look cool, or are hard to interpret

Interpretation is a huge part of it

Most of the linkage analyses and inspect what is happening with the physiological data

It is a nice visual effect

See what is going on related to the data

The child took off or was moving the sensor so that is not valid data

No current data

Overall Reflection

- If there was one thing you could change to make your life easier, what would it be?
- Tools? Workflow?

What additional information would you like to share with us?

All in one process with exports of raw data

If all the process could be in one that would be incredible

There may be visual I don't even know about

Visuals that would be helpful for external stakeholders

Easy visuals for parents to understand

Show areas of strong interaction or areas of improvement

Being able to pull out both

Visual and physiological to add two objective ways to measure the data

Anything easier?

Having it all in one

The only think I was thinking of, right now I look at EDA but it would be nice if it checked other physiologic measures

Video biofeedback

Will show Yuna's program to a colleague who is a parent and psychology colleague

Appendix B: Task Analysis

The task analysis steps included 1.transcribing interview notes, 2. task translation, 3. task sorting, and 4. task extraction and analysis. See image below.

Interview Notes Step #1
Add Sticky notes here for interview notes
Interview Notes
Stakeholder role: researcher and assistant prof at KU Medical center in dept of pediatrics
Stakeholder role: researcher in child autism and eating behaviors, physiologic linkage with parents
Stakeholder background: occupational therapy
Stakeholder role: Some of her work includes behavioral health coaching for how parents respond to children
Primary research populations: Children (with and without autism) and parents
Primary research goals: record child interaction w/ parents during play/meal times
Methods Step 0: Sync all recording devices
Methods Step 1: Clean data and code DINE
Methods Step 2: Generate and assess visuals
Current visual inventory: EDA graph overlay to videos
Current visual inventory: Wavelet and lattice charts
What is missing: More rich info from 1 view or platform (linkage variables, points of interest, summaries)
What is missing: Want to be able to distribute externally to parents and PCIT clinicians
Current tools: R, 3 python Shiny Apps, maybe Yuna's tool
Values of current tools (including Yuna's): many vars in 1 place, point-and click sync w/ video, sync with video
Pains of current tools: limited data, separate from video, want to jump to points of interest, don't want it to be messy
Wants: increase interpretability, esp in wavelet and lattice charts
Wants: support analysis of linkage and visually inspect how data corresponds to video
Wants: quicker and automated analysis (jump to points of interest, get summary stats)
Wants: More ways to visualize data, including easier charts for comms with parents
Wants: bio-feedback to establish behavioral patterns and triggers. Parents can learn from the data
Task Translation Step #2
We Sorted the interview notes into actionable items and what the stakeholders are looking for
This task is required but already externally supported
Task Translation
Generate Digestable Visualizations for Parents/Patients
View points of interest (highest / lowest linkage) within data
Generate Summary of the Data
Data cleaning
Overlay visuals with video footage
Generate visual of physiologic data - Electrodermal Sensor and other types
Synchronize the data sensor and video data
Make wavelet and lattice charts more interpretable
Support visual analysis of linkage within video footage
Support bio-feedback for tracking triggers and progress
View points of interest (leading/lagging) within data
View points of interest (magnitude of linkage) within data
Support auto-jumping to points of interest in video
Supporting quicker visual generation
Provide parents with insights from visuals
Supporting annotations (automated video interpretation vs. manually entered)
Analyze Parent Child Interactions
Behavioral Coding
Communication with Parents and Clinicians
Finding/Sorting an overview of points of interest in the data
Support analysis of linkage
Coorelate video behaviors with physiologic data (visually)
Task Sorting Step #3
Theme Identification
Task Sorting
Search (Locate)
View points of interest (magnitude of linkage) within data
View points of interest (leading/lagging) within data
View points of interest (highest / lowest linkage) within data
Generate visual of physiologic data - Electrodermal Sensor and other types
Query (Compare)
Search (Browse)
Overlay visuals with video footage
Support visual analysis of linkage within video footage
Coorelate video behaviors with physiologic data (visually)
Support analysis of linkage
Analyze Parent Child Interactions
Analyze Produce (annotate)
Analyze Produce (derive)
Supporting annotations (automated video interpretation vs. manually entered)
Behavioral Coding
Data Preparation & Synchronize
Synchronize the data sensor and video data
Data cleaning
Analyze Consume (Present)
Communication with Parents and Clinicians
Generate Digestable Visualizations for Parents/Patients
Make wavelet and lattice charts more interpretable
Provide parents with insights from visuals
Support bio-feedback for tracking triggers and progress
Generate Summary of the Data
Supporting quicker visual generation
Query (Summarize)
Support auto-jumping to points of interest in video
Finding/Sorting an overview of points of interest in the data
Search (Locate)
Query (Identify/ Compare)
Task Extraction/Analysis Step #4
Task Extraction/Analysis
Domain Task
Query Task (Low Level)
Search Task (Mid Level)
Analyze Task (High Level)
Make existing charts more interpretable
Consume (Present)
Analyze Parent Child Interactions
Consume (Discover)
Support auto-jumping to points of interest in video
Locate
Generate Summary of the Data
Summarize
View points of interest (highest / lowest linkage) within data
Compare
View points of interest (leading / lagging participant) within data
Locate / Identify
Coorelate video behaviors with physiologic data (visually)
Produce (annotate)
Support bio-feedback for tracking triggers and progress
Consume (Present)
Sorting points of interest in the data
Identify and Compare

Appendix C: Preliminary Sketches

From our six initial sketches, we selected three design components to further develop: the glyph in Figure 5, which supports comprehension of linkage data aligned with video footage and makes it easy to see linkage magnitude as well as leading and lagging participants; the heat map overlay in Figure 2 paired with with the point-and-click markers in Figure 6 to provide a summary of the linkage data and support linking video footage to key data features; and Figure 3, which helps generate data summaries, identify leading and lagging participants, and provide biofeedback and progress markers.

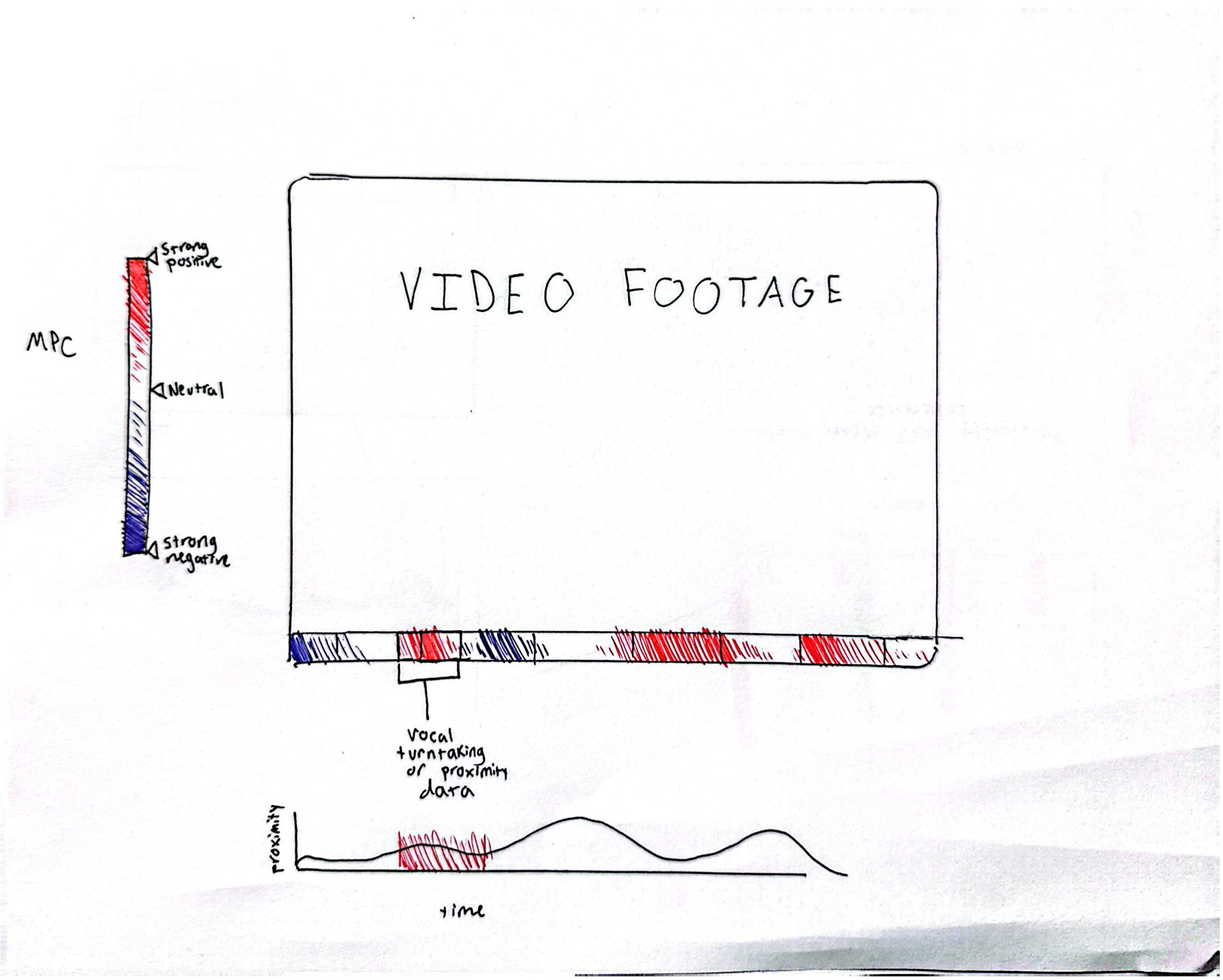

Figure 14: Sketch #1: - This first design is a simplified version of the area chart visualization in the third sketch (Figure 4). It encodes the magnitude of the mean phase coherence using a diverging color scale as an overlay on the video navigation panel. This provides a very basic overview of the synchrony data and stability while highlighting key points of interest within the video footage. It can be supplemented with a tooltip on hover to provide more details. It can also include a line graph of time-series data for additional features of interest, such as proximity, again using horizontal and vertical position to encode magnitude. These visuals address the tasks of making existing charts more interpretable and analyzing parent-child interactions. On a lower level, they support viewing linkage magnitude within data connecting the data to the video feed.

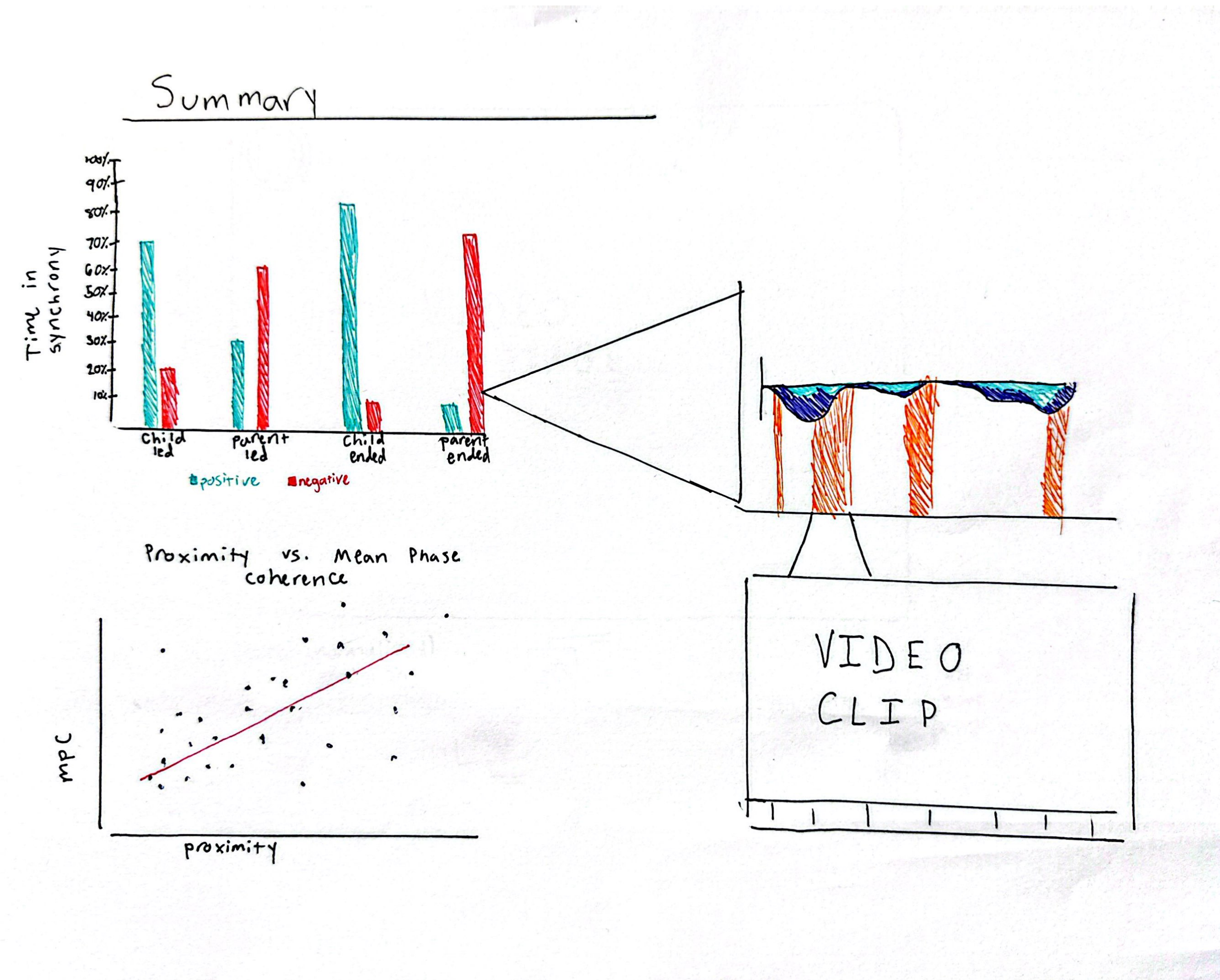

Figure 15: Sketch #2: - This dashboard features up to 3 visualizations to create a summary of the data, which also supports brushing, linking, and filtering to the area chart visualization from design 1. The first visualization is a grouped bar chart which displays four potential categories of interest: child-led into synchrony, parent-led into synchrony, child-led out of synchrony, and parent-led out of synchrony. Within each category, there is a bar for positive synchrony instances and negative synchrony instances. Color is used to encode positive versus negative synchrony, and length is used to encode the percentage. Upon clicking on a bar, an additional view will display of the area graph, filtered for only the type of synchrony that was selected (positive or negative), and highlighted for the category chosen (i.e., if a negative bar in parent-led synchrony is chosen, then only instances of the parent leading negative synchrony will be highlighted). A clip of the data at each highlighted point can also be displayed. Below this, a scatter plot of two quantitative data types, proximity versus mean phase coherence, shows the relationship between the physical closeness of the child and parent and their physiologic synchrony using horizontal and vertical positioning. A linear trend line is added to allow parents to see if there is any correlation between the two measure for their interactions. These visuals address the task of analyze parent-child interactions, support auto-jumping to points of interest in the video, summarize the data, and view leading and lagging participant within linkages.

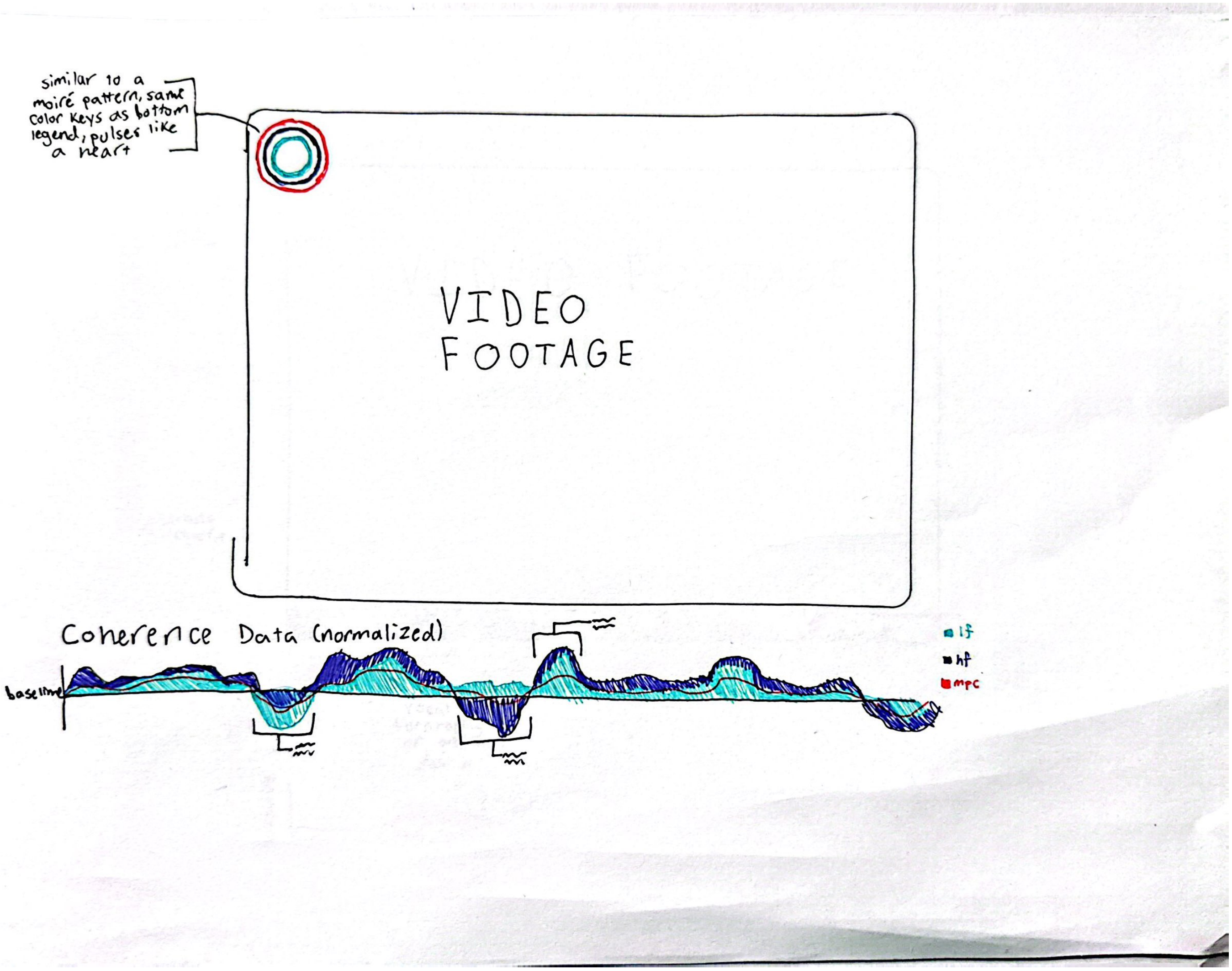

Figure 16: Sketch #3: This dashboard features 2 visualizations: a stacked area graph (similar to a stream graph) and a moiré pattern. Together, these visualizations encode coherence data (low frequency, high frequency, and mean phase coherence). They support the high level tasks for making existing charts more interpretable, and analyze parent-child interactions. On a lower level, the area chart supports viewing linkage magnitude within data, and both support connecting the data to the video feed. The moiré pattern visualization uses lines as the mark and width (or length) of each ring to encode the synchrony magnitude at each second in the video. The attributes (low frequency, high frequency, and mean phase coherence) are encoded using color and position, or where the ring is located in the patter. The objective of this visual is not to convey precise information, which can be found in the stream graph, but instead to offer a simple virtual cue within the video footage of what is happening in the data, and it mimics a heartbeat. The area chart uses color to encode the attributes of the data as well, and uses area below or above the baseline x-axis to encode positive or negative synchrony magnitudes within a given time period. The mean phase coherence is encoded as a line which uses position to depict the mean or stability of the synchrony. These design choices are appropriate for the mix of quantitative, time-series, and categorical data with the objectives being to present to a less scientific audience.

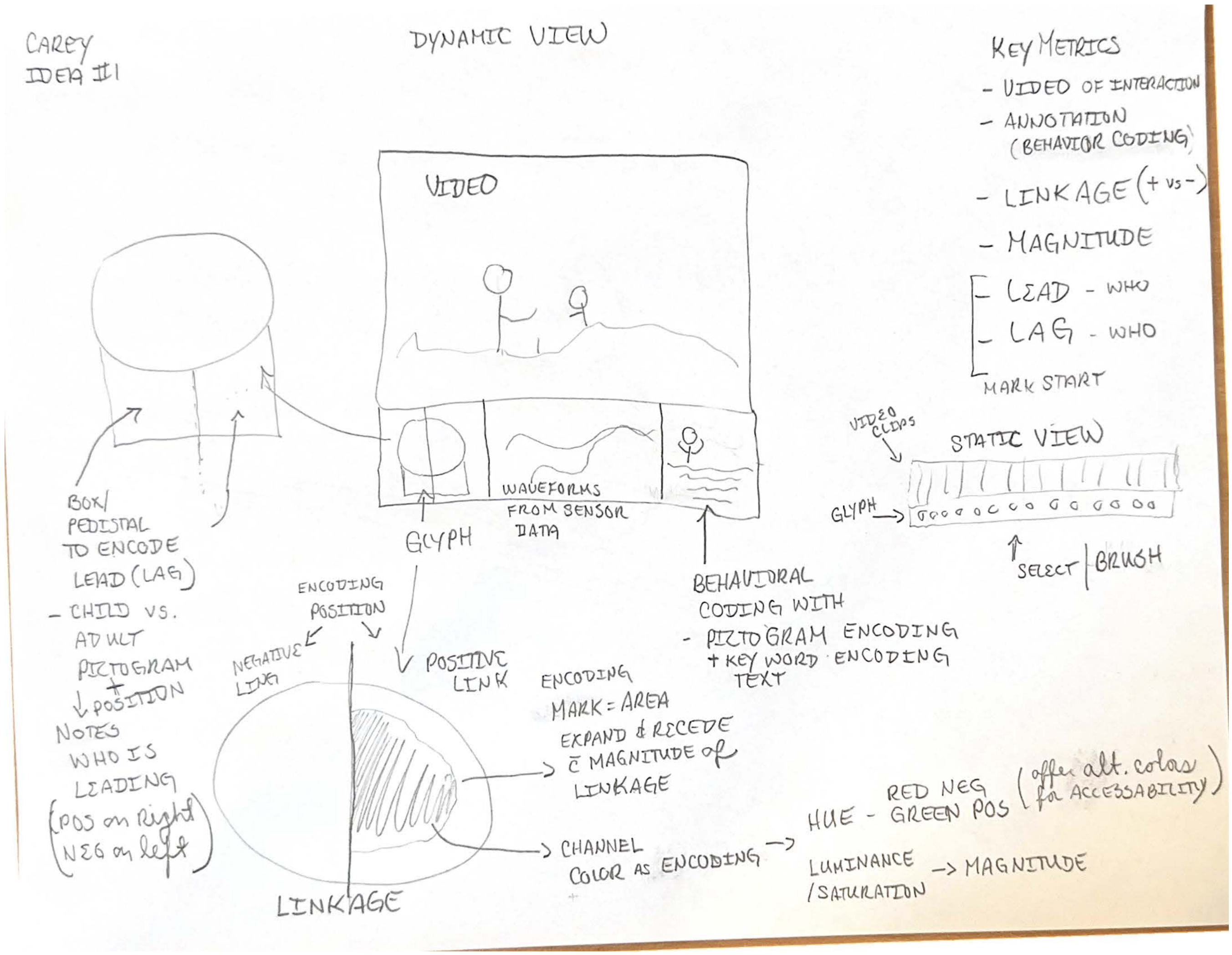

Figure 17: Sketch #4: Physiologic synchrony

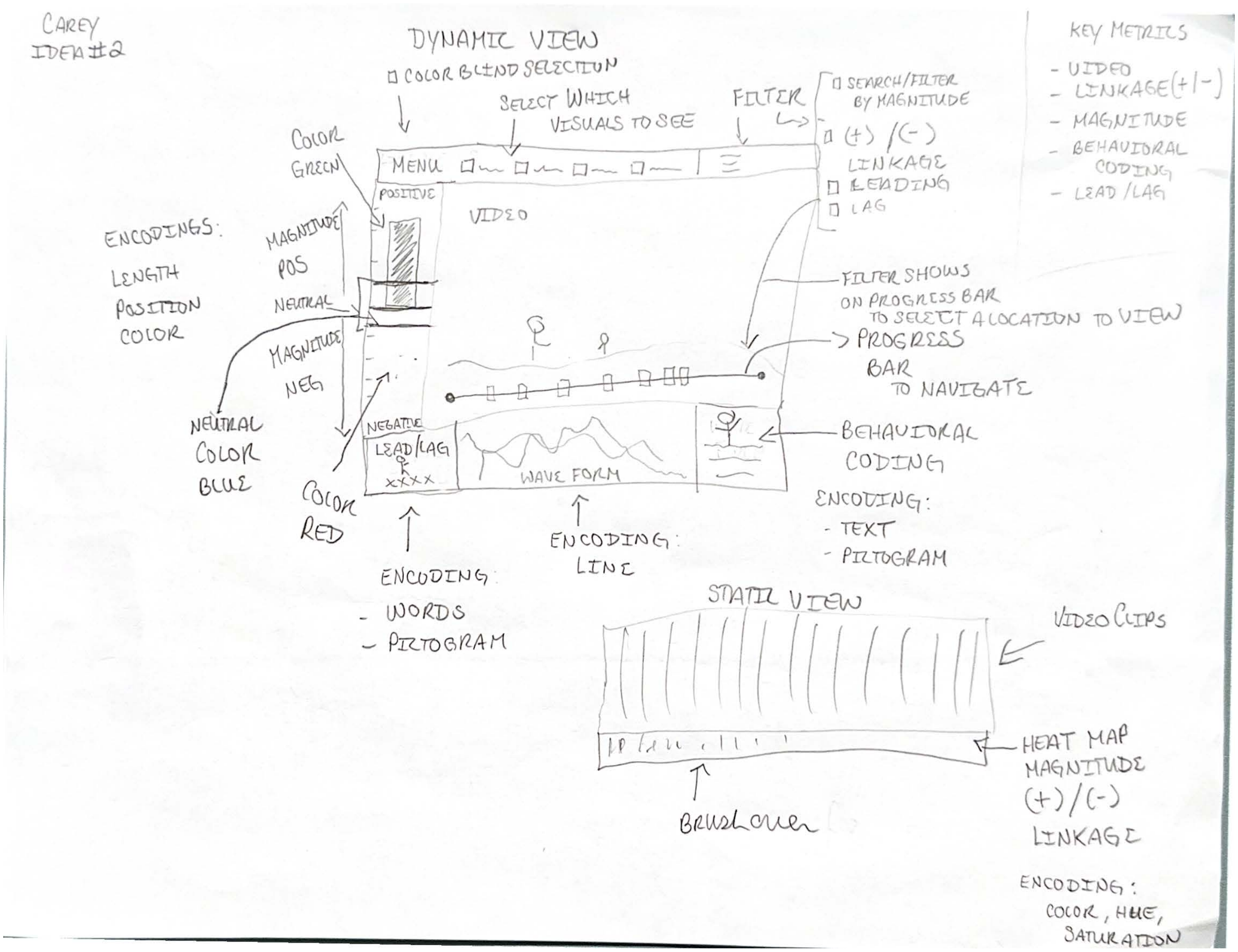

Figure 18: Sketch #5: Physiologic synchrony

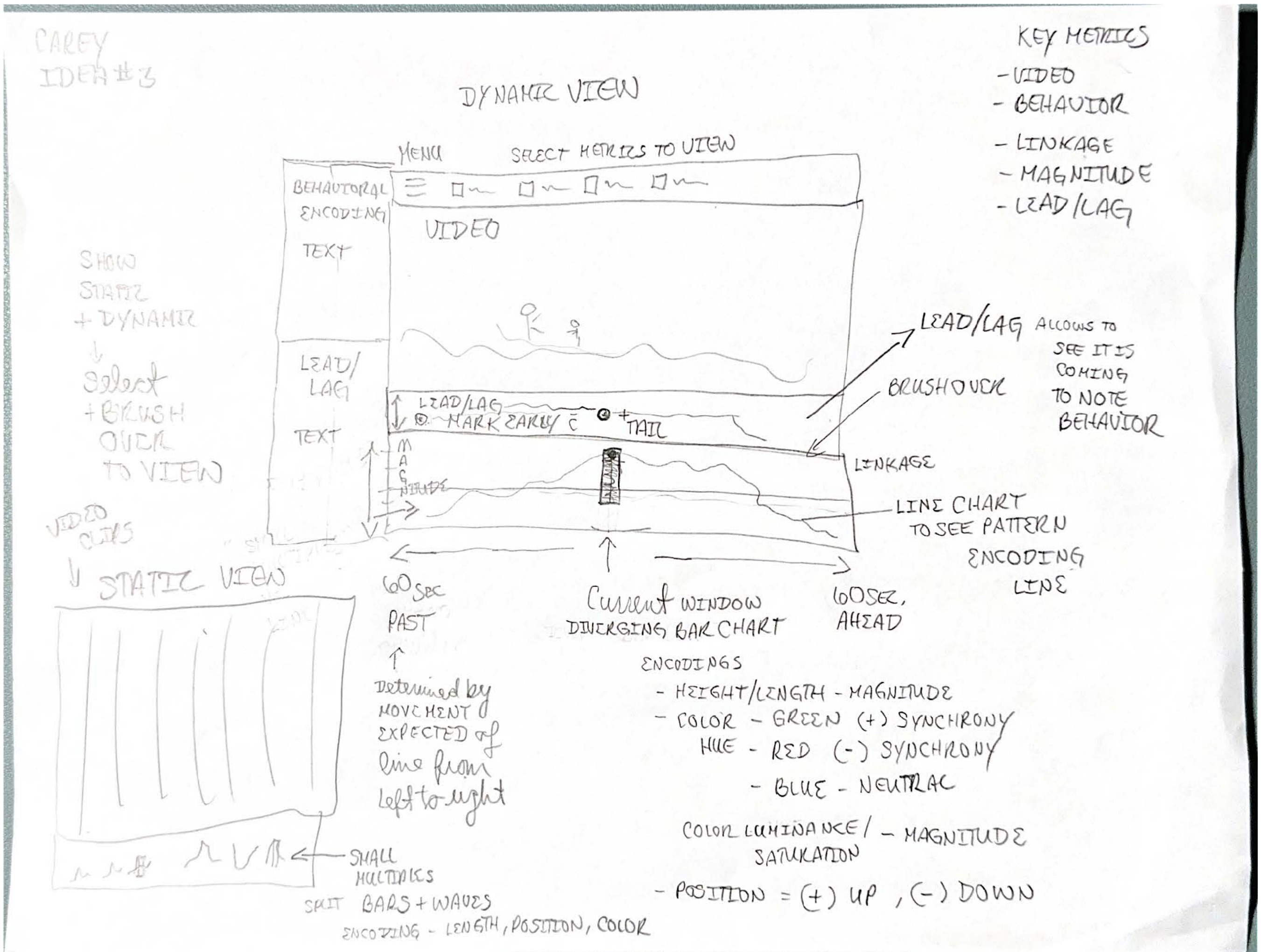

Figure 19: Sketch #6: Physiologic synchrony

Appendix D: Data Exploration Visuals

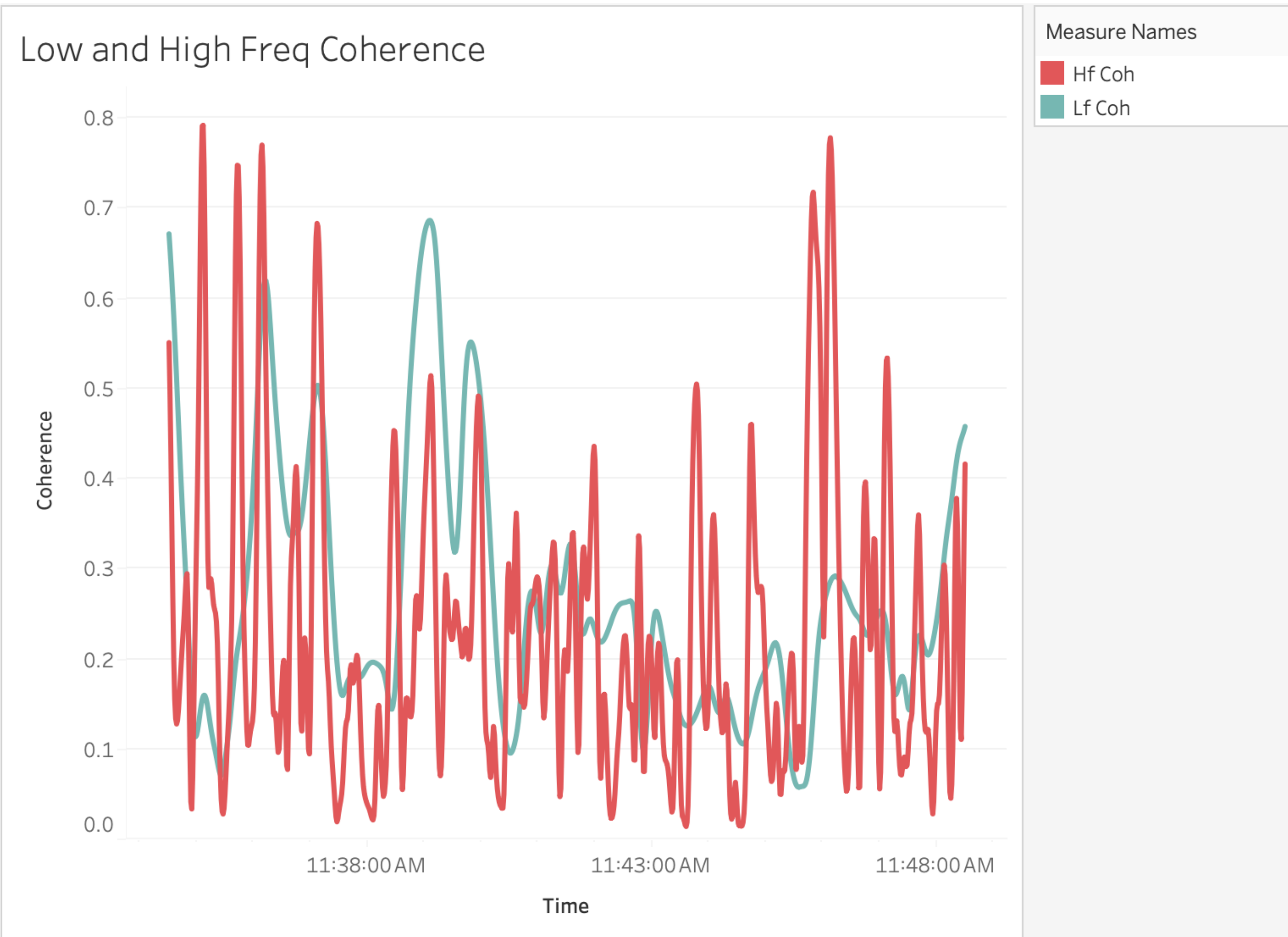

Figure 20: An exploration into the shape of the coherence variability for low and high frequencies across the same time. There is much greater variability in Hf Coh, though both seem to generally move in the same direction.

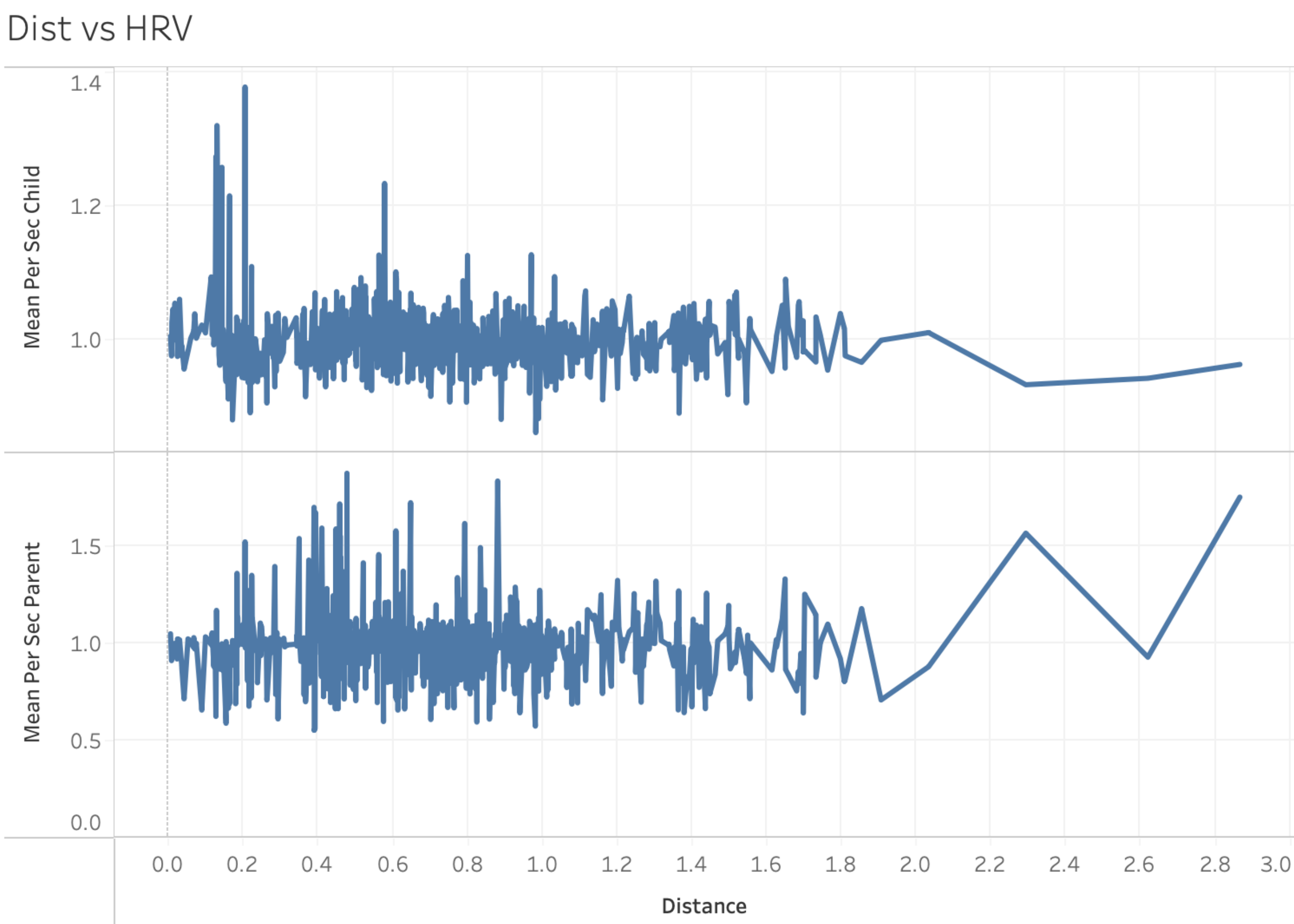

Figure 21: An analysis of heart rate variability in parent and child versus their distance. No significant trend identified.

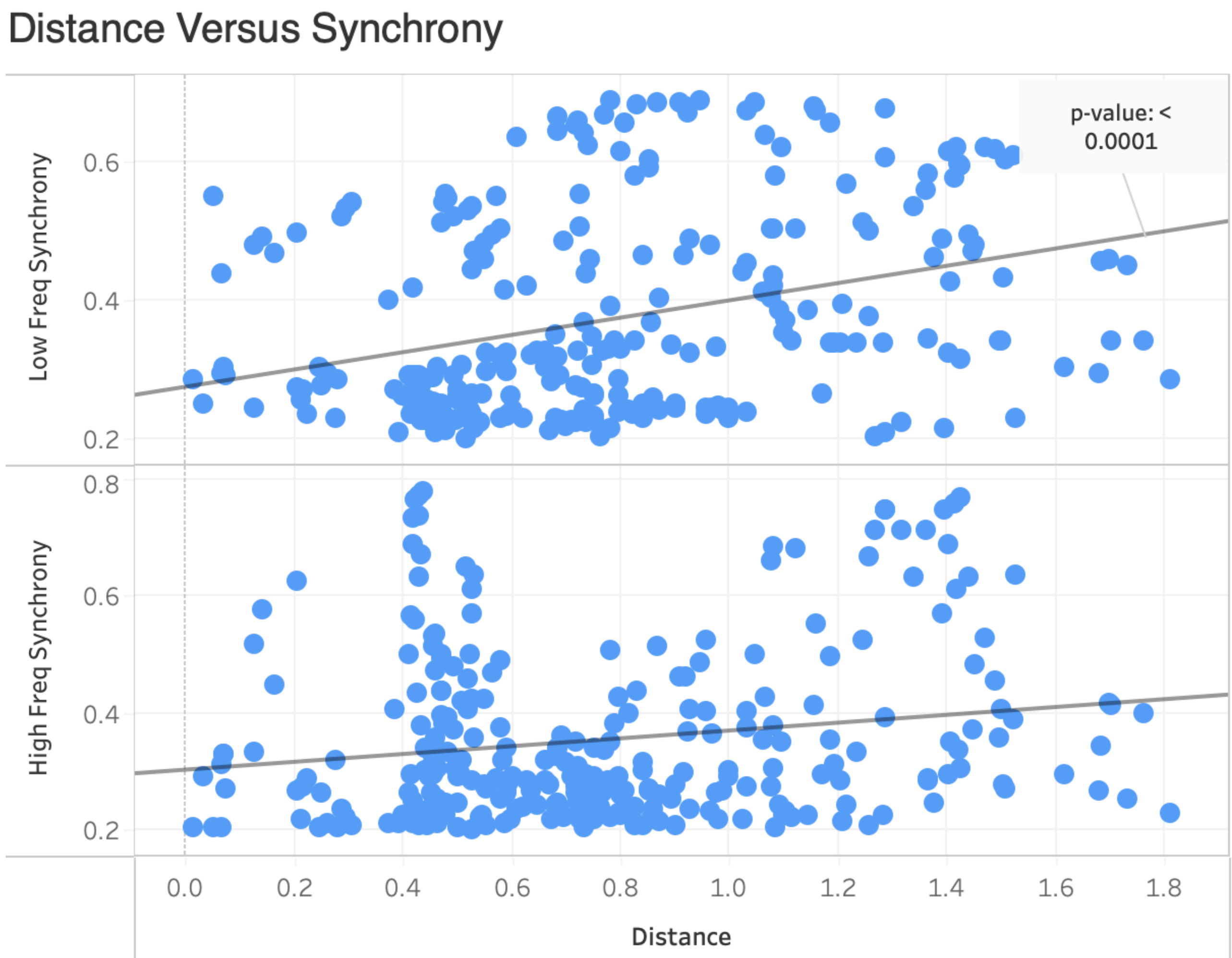

Figure 22: A look into how high and low frequency coherence values vary with distance. Two statistically significant (p-value $\leq$ 0.5) positive linear trend lines were created.

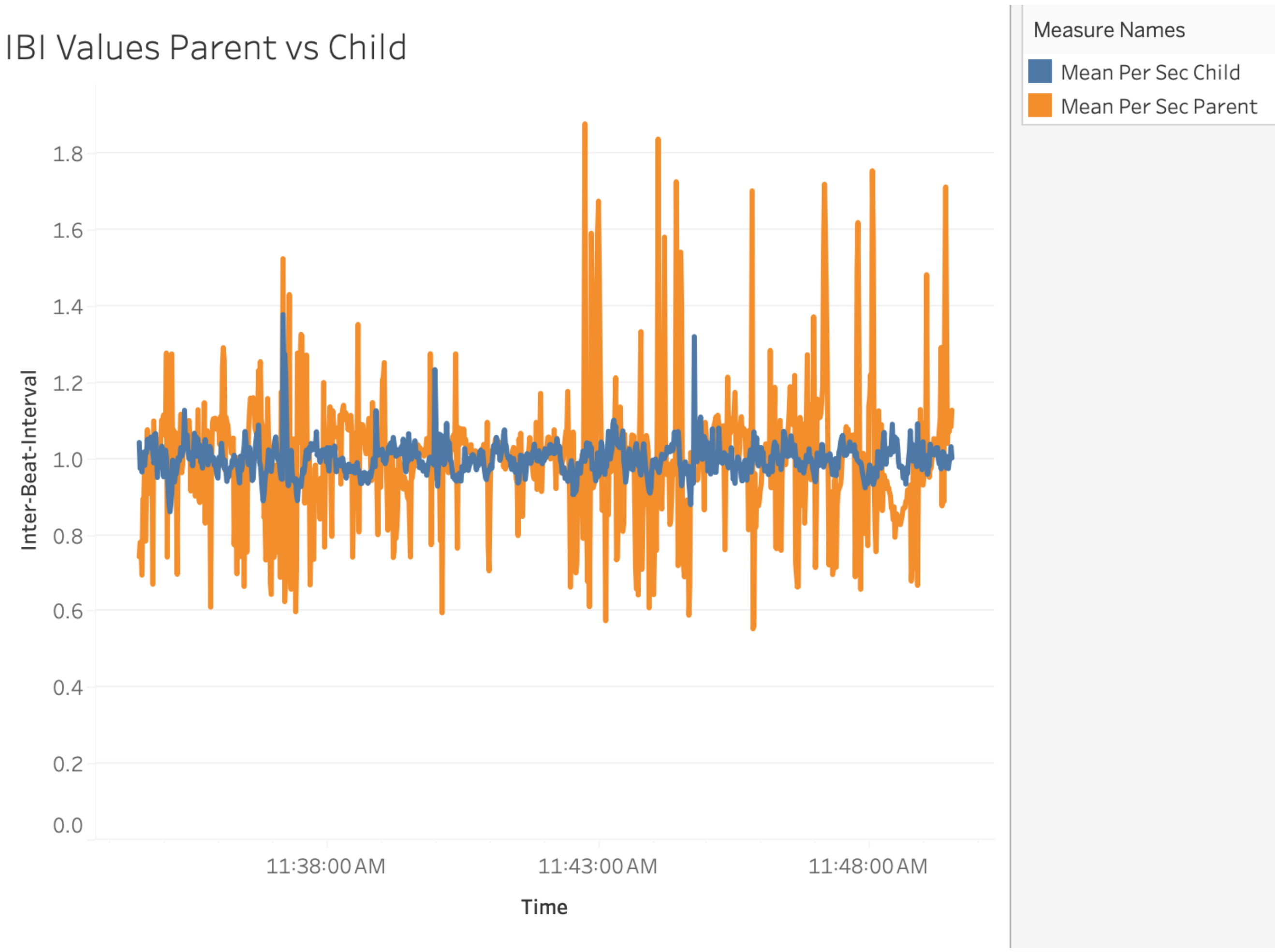

Figure 23: An exploration into the shape of the parent and child normalized interbeat intervals.

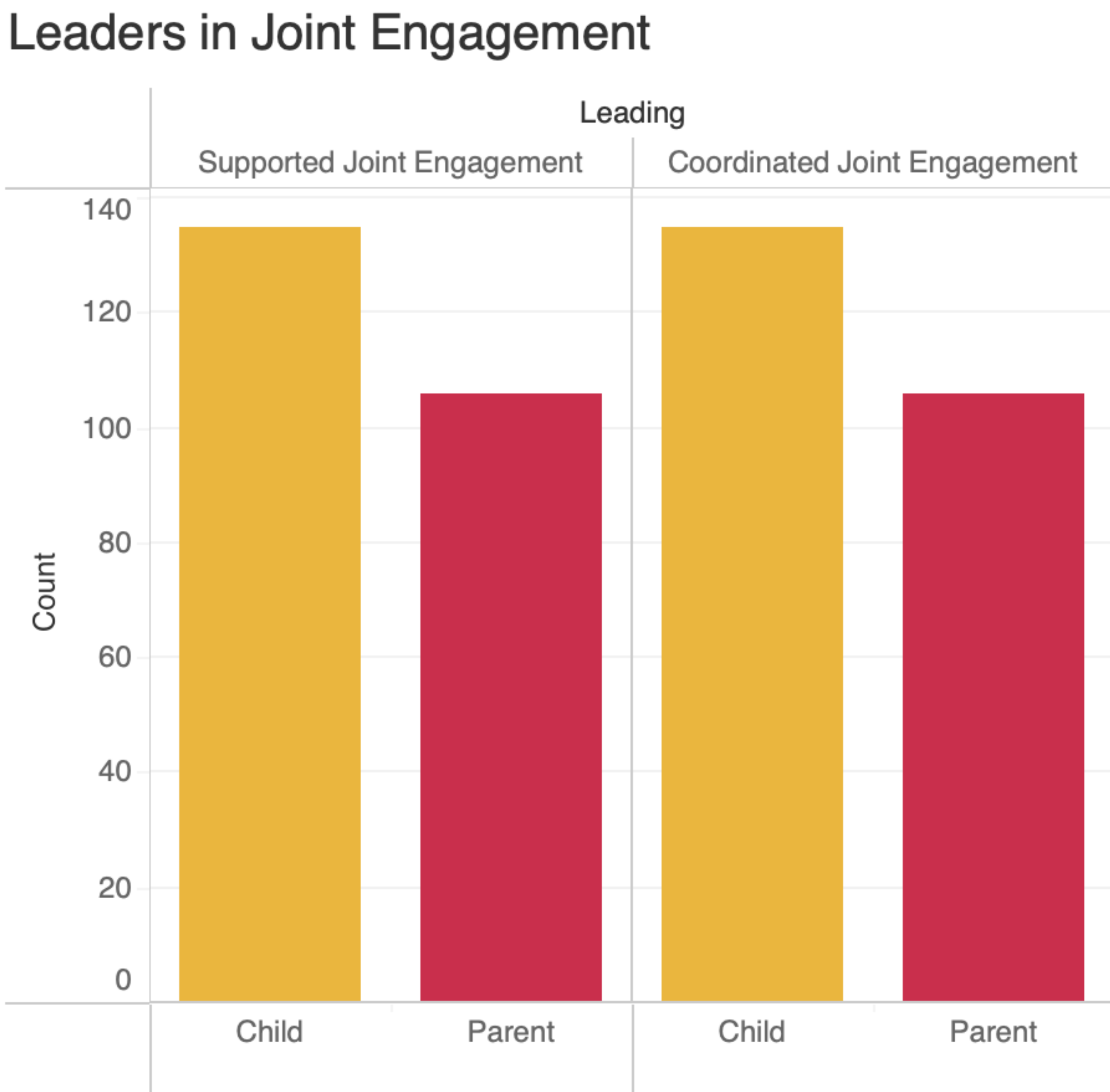

Figure 24: An exploratory graphic and potentially included visual in our summary page, showing the leaders in synchrony at periods of joint engagement.

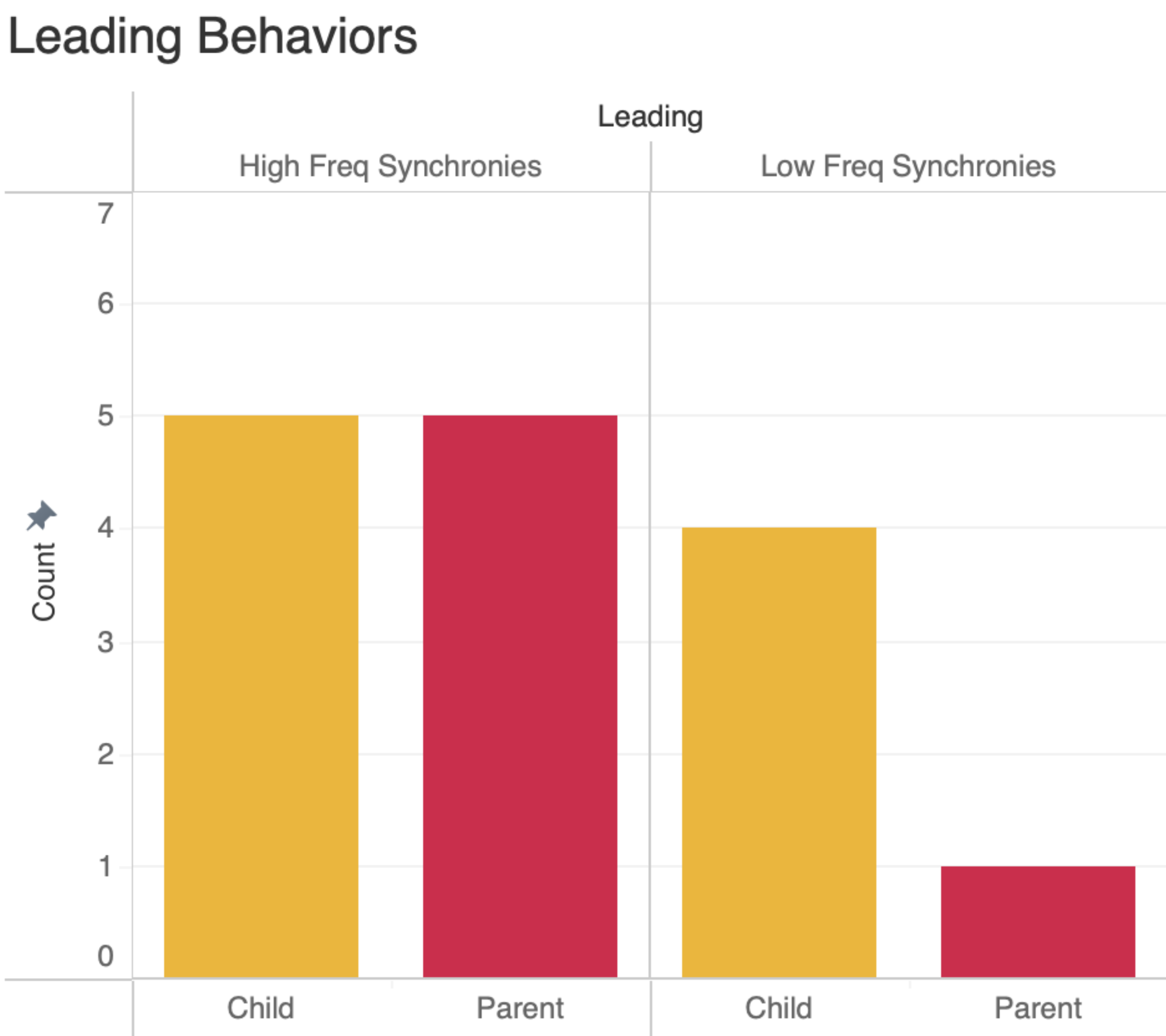

Figure 25: A composition of who led consecutive moments of synchrony within the data.