Body Gesture and Head Movement Analyses in Dyadic Parent-Child Interaction as Indicators of Relationship

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Abstract— **Parent-child nonverbal communication plays a crucial role in understanding their relationships and assessing their interaction styles. However, prior works have seldom studied the exchange of these nonverbal cues between the dyad and focused on isolated cues from one person at a time. In contrast, this work analyzes both parents' and children's individual and dyadic nonverbal behaviors in relation to their four relationship characteristics, i.e., child temperament, parenting style, parenting stress, and home literacy environment. We utilize a state-of-the-art feature selection framework on a dataset of 31 parent–child interactions to automatically extract and select a set of temporal nonverbal behaviors as key indicators of the dyad's relationship characteristics. The results show that relationship characteristics were associated with both individuals' and dyads' nonverbal behaviors. This finding highlights the importance of accounting for both individual- and dyad-scale nonverbal behaviors when predicting dyadic relationship characteristics as well as the potential limitations of utilizing single persons' nonverbal data in isolation. It therefore motivates future work on this topic to take a holistic and relational approach. The dataset and extracted nonverbal data are made public to aid the development of automated detection tools for parent-child relationship characteristics that trains on visual recordings of their dyadic interactions.**

I. Introduction and Background

The quality of parent and child interactions plays a crucial role in child development and provides clues to understanding children's behavior [15]. To assess the quality of interaction and the parent-child relationship, previous works have studied parent-child interactions in various contexts (e.g., free play) and with respect to age (e.g., infant to adolescent) as well as for different physical and mental health conditions [9]. Nonverbal behaviors expressed through body and head movements carry considerable information about an individual's affect [16] and the interpersonal dynamics in a multi-person interaction [17]. Additionally, parent-child nonverbal behaviors have been used to understand a dyad's synchrony [14], attachment [4], and relationship [9]. Overall, prior work suggests that studying nonverbal cues plays an important role in assessing parent-child interactions, and can help develop assessment tools for developmentally appropriate parent-child interactions [5].

Facial expressions, body posture, gestures, vocal paralinguistics, interpersonal distance, and touch have been widely investigated as nonverbal cues when assessing parent-child interactions. However, the majority of prior works have only analyzed these nonverbal cues on an individual scale (either the child's or the parent's) rather than how they elicited in relation to each other [9], [16]. When analyzing child temperament, for example, it is beneficial to assess the parent's nonverbal behavioral responses to the child's behaviors, i.e., parent-child dyadic behaviors, to gain a holistic view of the interaction style. Also, most of the research in the field has been focused on infants younger than 12 months, since at this age nonverbal cues are the main communication channel between the parent and the child. A recent review showed only a few studies have examined nonverbal behavior as an assessment tool for children older than 12 months in relation to theories of attachment and child development [9]. To the best of our knowledge, the nonverbal behaviors (including turn-taking, gestures, etc.) that were assessed in the majority of these studies were manually annotated by human observers, which can be burdensome –except for paralinguistic features, e.g., pitch, voice tone. Furthermore, each study only inspected one assessment at a time (e.g., child temperament), which might limit the development of a holistic view of parent-child relationships and interaction styles.

Given the importance of nonverbal communication during parent-child interactions, and considering the gap in the previous work, we chose to explore how individual- and dyad-scale nonverbal behaviors were linked to various measures of parent-child relationship characteristics. Specifically, we investigated parent-child nonverbal cues in relation to their relationship characteristics, including child temperament, parenting style, parenting stress, and home literacy environment. The main contributions of this paper are as follows:

- We evaluate parent-child relationship from the perspective of nonverbal behaviors on an individual- and dyad-scale using multiple assessment tools.
- We automatically extracted and analyzed the broadest array of high-level temporal behavioral features to date associated with the parent-child interaction.
- We show the contribution of both individual- and dyad-scale nonverbal behaviors as indicators of parent-child relationship characteristics, and suggest a holistic and relational approach for future nonverbal analyses in dyadic interactions.
- To encourage more research on nonverbal parent-child dynamics, we make the extracted nonverbal features from this work and the DAMI-P2C relationship characteristics data publicly available. [1]

II. Method

A. Dataset and Parent-child Relationship Characteristic Scales

We used "dyadic affect in multi-modal interaction - parent to child" (DAMI-P2C) dataset that was introduced in [7], [6]. DAMI-P2C dataset presents story-reading interactions between parents and their children (ages 3–7) in a lab setting. It includes 31 parent-child pairs engaged in two story-reading sessions, each lasting 20–30 minutes, with self-report parent-child relationship surveys. In each video, the parent and the child sit next to each other and read books on a tablet. The average ages of the parents and the children are $39.70\pm$

§ Equal Contribution

[1] To download the data, please visit shorturl.at/djuES

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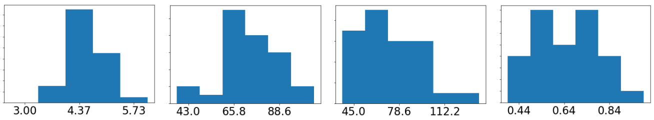

(a) CBQ **(b)** PRQ **(c)** PSI **(d)** HLE

Fig. 1: Distributions of parent-child relationship characteristics along with their Mean±SD, Min-Max, and scale score range. CBQ (4.57 ± 0.50; 3.61-5.42; [1.0, 7.0]]). PRQ (74.00 ± 14.52; 43-99; [0, 180]). PSI (73.20±19.76; 45-128; [36,180]). HLE (0.65±0.14; 0.44-0.93; [0,1.0]).

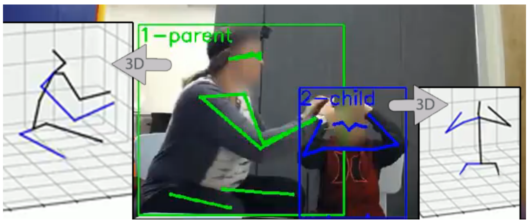

Fig. 2: Pre-processing steps including body detection, tracking, identification, and 3D triangulation from 2D joints extraction.

5.47 and 5.49 ± 1.37, respectively. Children's gender distribution is 21 male and 10 female, and parents are nine fathers and 22 mothers.

The self-report parent-child relationship survey includes Child's Behavior Questionnaire (CBQ) [19], Parenting Relationship Questionnaire (PRQ) [13], Parenting Stress Index (PSI) [1], and Home Literacy Environment (HLE) [23] scores. The dataset shows a spectrum of child and parental relationship scales as depicted in Fig. 1. The **CBQ** questionnaire [19] assesses a child's temperament in early to middle childhood; a higher score represents a higher level of negative temperament. As shown in Fig. 1a, the CBQ distributions were not heavily skewed toward either extreme, which indicates that the children in the dataset tended to have moderate temperaments. The **PRQ** questionnaire [13] measures a caregiver's parenting style; higher PRQ total score represents higher parental attachment, discipline, involvement, and confidence, as well as lower frustration. The **PSI** questionnaire [1] measures a level of parenting stress; higher PSI score represents higher parenting stress level. As shown in Fig. 1c, the distributions were skewed toward low levels of parenting stress. The **HLE** parameter captures a child's home literacy environment, with higher HLE score representing better home literacy environments. The HLE distribution in Fig. 1d demonstrates that the participants' home literacy environments in the dataset varied.

B. *Dyadic Nonverbal Cue Extraction*

1) Pre-Processing: To collect the dynamics of the participants' body movements – individually and in relation to each other – we performed an analysis in which the parents' and children's bodies and nonverbal behaviors from head and body movements were identified and continuously tracked. Using the front-camera view of the main video from the DAMI-P2C dataset, we first extracted the **raw locations of body joints** in every frame by i)detecting human bodies [20], ii) continuously tracking the detected bodies [25], iii) assigning identification to the tracked bodies, iv) extracting 17 body joints in 2D space [10], and finally, v) estimating the 3D triangulation from the 2D points [18]. It is worth noting that the 3D triangulation only estimates body poses given the 2D points, without depth estimation (see Fig. 2).

2) Low-Level Features Extraction: Once the joints were extracted, we calculated the (per frame) **low-level features** of individual body gestures, as well as their interactions with each other.

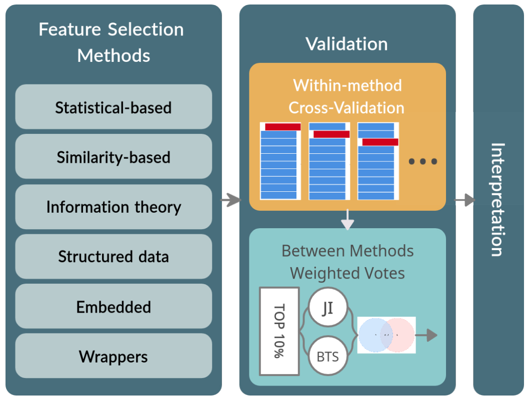

Fig. 3: The Feature Selection Framework – systematically aggregating the selected features from each method in two-validation steps; within and between methods; for final interpretation

First, we **normalized** the body sizes to account for both the within (e.g., distance from the camera) and between participants variations (e.g., differences in parent and child body sizes and between videos). This type of normalization assures reliable measures of the extracted features and a comparability of the analysis. In this work, we used the distance between the sternum point location and the collarbone (clavicle) points to normalize the distance between the other points (i.e., their distance is divided by the distance between two given points). We selected these two points for the normalization as they are rigid, which made them robust even through continuous, sudden, and skewed movements. Normalization was performed for each frame, after which we used Grubbs' test to detect outliers [11], which allowed us to remove any frames with skewed measures (e.g., erroneous joint location).

Based on the normalized body joints, we extracted individual and dyadic **body and head features** at every frame. By solving the direct linear transformation, followed by Levenberg-Marquardt optimization [22] from selected 3D points from individual bodies, we estimated the **chest and head orientations** (pitch, roll, and yaw) from the camera focal length. We extracted the parents' and children's chest and head orientations in relation to each other by calculating the Euler angles from selected points of both bodies.

We calculated the distance of the parents' and children's body centers and head centers (i.e., nose points) to determine **interpersonal space**, and we examined **touching behaviors**, including touching self-hands, self-face, self-upper body, we also examined the same for other touching behaviors (e.g., parent touching child's face, child touching parent's hand). This process resulted in 42 low-level features per frame.

3) High-Level Features Extraction: Finally, we summarized the signal by extracting the **functional features** over each video (i.e., high-level features per interaction session). We applied the functional features to the low-level features, as well as their derivatives (velocity and acceleration), to capture the duration of nonverbal behaviors. We extracted 10 functional features from each of the 42 low-level features and their derivatives, which included minimum (min), maximum (max), range, average, standard deviations (std), variance (var), skewness, kurtosis, peaks, and valleys. This process produced a total of 1,260 functional features (10 functional $\times$ 42 low-level $\times$ 3 signal and derivatives).

4) Feature Selection: To narrow down the feature space to the most meaningful and representative behaviors, we used a rigorous and comprehensive **feature selection framework** (proposed in [2]) to systematically determine the top behaviors that were correlated to the independent variables (i.e., the relationship characteristics). This framework served as an interpretation tool, not only by analyzing the features independently –i.e., finding statistical significant correlation– but also by analyzing the relationship between the features -e.g., removing redundant features, finding a combination of features that correlate together, etc. Given the large feature space for the analyzed nonverbal behaviors and the rather small sample size (62 sessions from 31 families), this feature selection framework is more robust in selecting the features than a simple statistical analysis (e.g., Pearson correlation) with multi-test correction (e.g., Bonferroni correction).

The framework selected the features by systematically aggregating the strong features within and between a wide range of feature selection methods, including statistical correlations (see Fig. 3). The **feature selection methods** ranged from statistics-based, similarity-based, information theory, structured data, embedded, and wrappers methods. Given the sensitivity of the feature selection methods to the sample size, the framework validated the selected features within each method through cross-validation. This is, for example for statistical methods, selecting the features with $p-$value above 0.05 in all cross-validation folds. We then selected the commonly-selected features for that method through the cross-validation rounds. For the **in-between methods validation**, the framework aggregated the selected features from all of the methods through stability measures; features were then selected based on weighted votes above a certain threshold –i.e., the features been selected by 90% of the methods. We used 11 feature selection methods for the investigated variables (e.g., CBQ, HLE, etc.), and for **cross-validation** we used 10-folds with two runs to measure both the Jaccard index and between threshold stability measures.

We divided the full feature space (1,260 functional features) into six sub-feature nonverbal behavior spaces: parent body and child body (240 features each), the dyads' bodies (480 features), and the parents' and children's heads (90 features each), and dyads' heads (120 features). This allowed us to interpret each sub-space behavior separately and prevented behaviors from one sub-space from dominating other sub-spaces (e.g., parent body movements could dominate their own or their child's head movements). We selected up to the top 10% of features from each sub-space for each independent variable. To provide an interpretation on the final selected features, we ran a correlation on each feature-relationship pair (either Spearsman or Pearson - depending on the normality of the feature) to determine its relational direction.

III. Nonverbal Analysis Results

As discussed in Section II-B.4, we analyzed the extracted nonverbal behaviors using the feature selection framework for interpretation. Our analysis results revealed interesting nonverbal behavior indicators of **child temperament**, **parenting style**, **parenting stress**, and **home literacy environment** measures, as listed in Table I.

Several **child** nonverbal behaviors were indicators of the **child temperament** measure. Long durations of looking down and leaning forward, as well as less frequent changes in body posture and head orientation, were found to be correlated to higher CBQ scores, i.e., the child's negative temperament and behavior. This might indicate the child's low-energy levels and less attentiveness to the parent and the activity due to the child's high negative emotion and low adaptability to the new lab setting, which are common characteristics of their difficult temperament [8].

On the other hand, **parent**'s body and head movement behaviors such as long duration, frequent, and fast leaning backward, were mostly negatively related to CBQ scores, which might indicate that

TABLE I: Interpretation of the selected nonverbal behavior features with parent-child relationship measures (+ indicates positive relation to the measure, and - indicates negative relation) – the results showed the contribution of child's, parent's and dyad's joint behaviors as indicators of the interaction style and relationship.

	Person	Nonverbal Behavior
CBQ	Child	+ leaning forward –prolonged duration
		+ body posture change –less frequent
		+ body movement –slow
		+ touching hands and body –less frequent; slow
		+ head orientation change –less frequent
		+ looking down –prolonged duration
	Parent	- leaning backward movement –continuous; frequent; fast
		- touching face and body –slow
		+ looking up –frequent
	Dyad	+ synced leaning forward –prolonged duration
		+ interpersonal space –large
		- synced posture change –frequent;
		- synced body movement –fast
		- synced body movement toward each other –slow
		- child touching parent's face and hands –frequent
		- parent touching child's face and body –frequent
		- heads distance –frequently closer
PRQ	Child	+ leaning forward –max angle
		+ touching face and hands –less frequent; short duration
		+ interchange between looking up and down –frequent
		- interchange between leaning forward and backward –continuous
		- body sides roll –short duration; frequent
		- touching face, body and hands –frequent and fast
	Parent	+ body posture change –short duration
		+ touching face and hands –less frequent; short duration
		+ side ways head movement –slow
		- body posture change –frequent; fast
		- touching face, body and hand –fast; long duration
	Dyad	+ synced leaning forward –slow and long duration
		+ synced bodies side roll –slow
		- posture change –frequent; fast; short duration
		- synced bodies side roll change –frequent
		- interpersonal space –small
		- child touching parent's face –short; frequent
		- parent touching child's face –short; frequent
		- hand holding –slow
		- synced looking up –prolonged duration
PSI	Child	+ leaning forward –frequent; slow; prolonged duration
		+ looking up –frequent
		- touching face, body and hand –fast; short duration
		- looking up –slow
	Parent	+ touching face touch and fast body –prolonged duration
		+ leaning posture change –frequent; fast
		+ looking up –frequent
		- leaning forward –speed range
		- leaning forward –duration range
	Dyad	+ interpersonal space –frequent being apart
		+ mutual gaze –minimum
		+ parent touching child's face –frequent
		+ leaning forward –frequent; fast; short duration
		+ synced body roll change –frequent; fast
		- hand holding –slow
		- child touching parent's face –frequent
HLE	Child	+ leaning forward –frequent; slow; short duration
		- leaning backward –prolonged duration
		+ touching hand –less frequent
		+ looking down –frequent; slow
		- touching face –frequent
	Parent	+ leaning forward –frequent; slow; prolonged duration
		+ touching body –fast
		+ looking down –frequent
		- touching face –fast; short duration
	Dyad	+ parent touching child's body –frequent
		+ interpersonal space –frequent change
		+ synced leaning forward –frequent; slow; prolonged duration
		- hand holding –fast; prolonged duration
		- child touching parent's face –slow; frequent
		- synced body roll change –frequent; slow

the parent's attentiveness behaviors to attract the child's engagement with the story reading are less challenging if the child has an easy temperament [24].Moreover, parents whose children had lower CBQ scores touched their faces and bodies more often and slowly, which might indicate self-soothing behavior. Such behavior are also related to low PRQ scores (explained below), which call for multi-factor analysis in future work. Parent's positive nonverbal behavior indicator of high CBQ scores was head looking up often, which could indicate efforts for eye-contact for interventions and correcting their child's impulsive behaviors given their child's difficult temperament [24].

Regarding the **dyadic** nonverbal behaviors, the prolonged synchronized leaning forward were linked with high CBQ scores, which could imply that the dyad might focus only on the storybook and lack back-and-forth affective communication with each other. On the other hand, frequent and fast body posture and head distance changes in both children and parents were correlated to low CBQ scores, which indicates that the child was able to seamlessly coordinate with their parent and achieve a high level of active joint engagement with the parent [21]. Similarly, slow body movement toward each other and parent's and child's mutual body and face touching were related to lower CBQ scores, which could indicate a high level of mutual intimacy and coordination.

The analysis on nonverbal indicators of the **parenting style** also yielded valuable findings. First, a positive link between **child**'s looking up head movements and high PRQ score was found, which indicated child's high attentiveness to the parent. The low PRQ score was related to both child's continuous interchange of body postures and self-touching, which indicated that the parent with low PRQ scores might have difficulty intervening on child's distraction and impulsive behaviors in the reading activity. The **parents**' self-touching and frequent body movements were found to indicate lower PRQ scores, which might signify their mental unease and awkwardness in the co-reading interaction. Finally, regarding the **dyadic nonverbal indicators**, low dyadic synchrony in body and head movements, frequent mutual face touching, and close interpersonal space were linked with lower PRQ scores, indicating similar patterns to child's behavior of low discipline and involvement styles.

The **parenting stress** measure shared similar nonverbal behavior indicators with the parenting style measure, probably because PSI and PRQ were moderately correlated with $\rho = 0.47$ [6]. The behavior indicators of high PSI scores included frequent **child** and **parent** body movements with short durations of **dyadic** synchronous body movements. Since these behaviors are often associated with one's distraction and low engagement in the activity, the findings revealed that the parent's parenting stress might also contribute to both the child's and parent's engagement levels. Furthermore, parent self-touching behaviors, frequently touching their child's face, as well as parent and child frequently looking up with minimum mutual gaze were linked with high PSI scores, which indicated that parents with higher parenting stress level tended to exhibit nonverbal cues of self-soothing and out of sync with their child's. These behaviors are in line with research on parent-child relationship, where the parent perception and satisfaction of their child's interaction, distractibility, and acceptability are assessed [12].

In terms of nonverbal behaviors associated with **HLE** scores, **children** with high HLE scores had frequent changes, slow movements, and short durations of leaning forward and looking down, which could be indications of positive involvement and engagement, and high adaptability to the lab setting given their familiarity to story reading activity. Further investigation of the multi-factors associated with such behaviors (e.g., cross-referencing with CBQ, PRQ, and PSI scores) should be performed to confirm these findings. On the other hand, **parents**' frequent and long duration of leaning forward and looking down behaviors were associated with high HLE scores; this indicated involvement with the reading material. Regarding the **dyadic features**, the frequent long synchronized leaning forward behavior and frequent close interpersonal space were both found to indicate high HLE scores. Children's and parents' self-face touching, as well as children touching their parents' faces, were correlated to low HLE scores. Family members touching each other is usually associated with positive emotions and closeness [3], which interestingly, was correlated to various measures in our analysis.

IV. Discussion and Conclusion

Overall, our analysis on nonverbal behavior indicators showed that both individual-scale and dyad-scale nonverbal behaviors contributed to identifying parent-child relationship characteristics. For each relationship characteristic, the set of nonverbal behavior indicators comprises of all body, head and hand modalities rather than from one single dominant nonverbal modality. These findings and insights emphasize the need to account for jointly analyzing multiple behavior modalities from both the individuals' and the dyad's to generate a holistic view of the overall parent-child interaction and its relations with the dyadic relationship. For example, future work on exploring the links between child's temperament and their social interaction should not just include child's nonverbal behaviors but also take parent's nonverbal behaviors and the parent-child dyadic mutual behaviors into consideration. Similarly, when collecting parent-child dyadic interaction datasets, future studies should make sure that the audiovisual recording environment and observation settings can capture the full view of the dyad's interactions including both parent's and child's view for later nonverbal analysis. We encourage future work to take a holistic and relational analysis approach even when the analyzed social profile measure concerns only one of the two people in the dyad, e.g., child temperament.

Furthermore, our interpretations on the nonverbal behavior indicators in Section III showed that the nonverbal features automatically extracted and selected by the feature engineering system could be externally validated in the psychology literature. Hence, our work confirmed the technical feasibility of developing fully automated computing tools that assess parent-child relationship characteristics via visual recordings of their social interactions.

We acknowledge the relatively small dataset of the dyad samples, which might limit the generalizability of specific nonverbal behavior links to parent-child interaction. However, this work only intends to show that both individual- and dyad-scale behaviors as well as diverse nonverbal modalities all necessarily contribute to characterizing dyadic relationships, thereby highlighting the limitation of nonverbal analysis approaches that focus on isolated cues from one person at a time. In future, we plan to use other parent-child interaction datasets to pinpoint how each nonverbal behavior is associated with the parent-child relationship. Moreover, we believe that besides long-term relationship measures for nonverbal analysis, short-term measures such as affective states and engagement of the parent and child can also allow for precise analysis of causes and triggers of certain nonverbal behaviors. In conclusion, this work serves as the first step toward developing a holistic relational approach for understanding and assessing the parent-child relationships and interaction dynamics via nonverbal analysis.

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