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RESEARCH PAPER

A formative evaluation of human activity recognition technology for parent-child interactions

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Abstract
Studies in recognition of human activities have been developed in populations of all ages. It is possible to use various technologies to obtain data from environmental sensors or equipment, such as wheelchairs or wearable devices, for everyday and specialized use. With children, using augmented toys has become one of the preferred mechanisms to obtain information about the interaction between children and the toy. However, few efforts have been made to study mechanisms for receiving data from child and adult interactions. This work presents the design and evaluation of a computationally augmented glove and puzzle piece based on the specifications from the literature. After the evaluation, we proposed changes to the glove design to ensure the correct interaction data was obtained.

Keywords:
Parent-Child Interaction; Activity Recognition; Wearable Sensors; Interaction-Monitoring; Augmented Garments; Wearables Design.

1 Introduction
Human activity recognition (HAR) analyzes sensor data to identify and characterize human activities [34]. HAR has been used to study subject-object interaction. HAR researchers often use wearable and mobile technologies to gather data needed for activity recognition [12].

Among different application areas, the use of HAR techniques for the identification/recognition of behaviors has become an interesting topic due to its potential to impact several research contexts, such as surveillance, healthcare, and Human-Computer Interaction [2, 16]. It offers a way to use automated mechanisms to obtain data under different conditions (e.g., laboratory, naturalistic environments) while performing other tasks (e.g., interacting with specific objects, doing a particular task, or in free play conditions) with minimal intervention by researchers, and with the ability to process the collected data faster than when using manual observational methods.

Several works have reported projects involving adults, young people [16, 34], and children [4] in the HAR area. For example, in the elderly population, there has been work on using HAR techniques for fall risk prevention [11, 30] and medication intake monitoring [33, 35], whereas for young people, fitness and wearable monitoring systems are widely studied [17, 18]. Typically, to collect data, researchers use a combination of non-intrusive sensors hidden in the environment (e.g., video cameras, hearing aids), sensors mounted on devices used by people (motion and pressure sensors on a wheelchair), sensors embedded in everyday devices such as phones and smart watches (inertial sensors) and sensors embedded in specialized devices such as heart rate bands [38].

For the children population, there is a growing interest in using HAR techniques to identify/recognize activities related to behaviors that can negatively affect the children's wellbeing, especially those with disabilities [6, 8, 37, 39, 42]. Among these behaviors, the researchers study not only individual children´s behaviors but also those that arise during the interaction of children and adults, such as children-teacher and parent-child interactions. Directive behaviors are one type of behavior exhibited by parents during parent-child interaction that could affect their children negatively, especially in the presence of a disability [1]. In the case of parents of children with disabilities, these behaviors are more marked compared to parents of neurotypical children.

Since most technologies used with adults and young have proven only partially suitable for children [31], it has driven the use of augmented toys to gather data for activity recognition when only children are participating [4]. Using augmented toys implies the analysis of data collected from one or several children interacting with one or more toys. When designing smart toys to obtain children's interaction data, selecting the type, size, and location of sensors becomes critical due to the importance of keeping the toy aspect and its attractiveness and joy for the child [5, 37].

However, when talking about parent-child interaction, the use of augmented toys in the detection of behaviors faces new challenges since it becomes paramount the study of what mechanisms can be used to obtain information from the interaction while supporting the children's play experience and the possibility that parents can join the activity [22].

In this context, we are interested in designing mechanisms to automatically collect data to identify activities in an environment where children and adults participate simultaneously (e.g., to recognize directive behaviors) and, to the best of our knowledge,

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well-established methods or tools for automatically identifying activities in parent-child interactions have yet to be developed [10, 22, 23].

Considering our interest in mechanisms to collect data from parent-child interactions, we present the technical design and evaluation of a child's glove and a puzzle piece based on the specifications of [22] and the glove's prototypes presented in [13, 24, 29].

2 Related Work

Analyzing children's interactions with everyday objects, such as toys or home furniture, has been identified as a potential way to identify possible disorders [39].

Several approaches have been implemented for the study of children's interactions. One such strategy is capturing and analyzing audio and video of children's daily activities [3, 7, 9]. Others tried using wearables to gather data [25, 27, 28], and several works aimed at studying the use of augmented toys as an alternative to avoid factors that affect previous approaches like video occlusion and tolerance to use wearables (especially by children with disabilities) [4, 36].

As physical manipulatives, augmented toys embody the physical interface by themselves [32]. Electronic and computational components allow toys to obtain information from their environment (e.g., temperature sensors, heart rate, pressure, inertial data), perform processing tasks (e.g., embedded microcontrollers), and provide feedback to the user (e.g., LED spotlights, speakers, vibrohaptic motors). For instance, in the work of [42], toys with embedded sensors are used to obtain data that identify children's play patterns, which can be early predictors of autism. An accelerometer, gyroscope, and a pressure sensor inside each toy constitute the primary means of obtaining interaction data. In the same way, Autoplay [8] is a toy kit that allows data generated during ludic activities to be obtained to anticipate the diagnosis of autistic disorders, neurological development, or social fragility. Internally, using an accelerometer, a gyroscope, a magnetometer, a barometer, a thermometer, and a temperature sensor allows each toy to sense the data to identify and characterize the behaviors of interest.

Another example is Guided play [6], a technology that uses augmented games and toys to identify repetitive and restrictive behaviors during play. The latter represents an early marker of autism and thus facilitates an intervention that can reduce these behaviors and promote symbolic play. Other researchers have focused on using construction block toys with different sensor types [15, 40, 41] that enabled indirect data as physiological children's parameters to derive child-object interaction information.

These works are essential evidence of the potential of using augmented toys to obtain interaction data in studies where the main actors are children, and the parents only support their children without direct intervention in the game dynamics. However, when a parent is actively playing with her child, the type of game is crucial in understanding parent-child interaction, as it must engage the child and encourage parent participation.

In this sense, puzzles are a well-known board game used to support problem-solving activities [19, 26, 43] and in prior research to investigate different behaviors in parent-child interactions [14, 20, 21].

The works of [10, 22, 23] study the use of augmented puzzles to gather data from parent-child interaction. In all studies, researchers used wooden puzzle boards to allow parent involvement.

In [22], researchers used the Wizard of Oz technique. To simulate an augmented puzzle board using a wooden jigsaw puzzle, two pairs of embroidered gloves equipped with simulated sensors, and a projector to display a virtual image of the physical puzzle before the parent-child dyad. This study reports a positive, playful experience with the augmented puzzle and the comfort of gloves. Other authors have focused on building augmented glove prototypes for applications in other areas. The different approaches used in equipping the gloves offer insights into the materials, shapes, and devices that can be used in implementing our prototype.

In [13], a prototype of a basketball glove is presented, aimed at obtaining data for the identification of different movements that a player makes with the ball: dribbling, passing, shooting, and slapping the ball. A fabric glove equipped with piezoelectric sensors placed on the fingertips was proposed, capable of identifying the pressures of the hand's fingers to identify pressure patterns for each movement. Considering the type of sensors used, the possibility of identifying the pressure exerted by each finger is similar to what happens when a child holds a puzzle piece.

To help patients with Parkinson's Disease (PwPD), in [29] a system was developed based on the use of two textile gloves to remotely monitor the hand movements of patients with difficulties to assist medical centers for periodical evaluation. Various hand movements are monitored, such as finger tapping, hand opening, and closing. The gloves are integrated with flex sensors on the fingers and one inertial measurement unit and have an onboard microcontroller connected wirelessly to a tablet computer. The system was assessed with four PwPDs, hand movement-related data was collected, and the system was able to identify differences in pre-medication and post-medication test. This is an example of the potential of flex and IMU sensors to identify finger and hand movements, which are essential if you want to detect when the glove is holding a piece and/or when the glove is moving.

Finally, in [24] researchers designed and built a glove prototype intended to recognize objects when performing basic daily activities. Unlike other approaches, the gloves have force, flex, and IMU sensors. This allows the use of pressure and flexion angle to identify the object's shape, and the IMU to determine if the object is static or in movement.

3 Implementing HAR technology for parent-child interactions

The work of [22] proposed using an augmented puzzle to obtain data on the interaction of a parent and her child with disabilities. The authors present a strategy for associating game activities with smaller steps that can be determined using data collected by the sensors embedded in the puzzle's pieces and into the participant's gloves.

For example, the activity "The Parent removes a piece from the puzzle board previously placed by the child" is divided into the following steps: (a) The parent takes the piece from the board and (b) The parent places the piece outside the puzzle board.

Following Figure 1, we chose a one-size-fits-all embroidered glove to fit children's hand sizes. The glove included custom-built pressure sensors based on the design of [44] and [13]. These pressure sensors were in the thumb, index, and middle fingers to detect when anyone touches an object's surface (Figure 1A). The same fingers had one spectra flex sensor to detect finger bending (Figure 1B). All components in the glove were connected using an electrically conductive thread.

On the other hand, the puzzle piece was built from PLA material using a 3D Creality printer. It is based on a rectangular prism form factor, 65mm(W) x 65mm(D) x 25mm(H). We wrapped the piece in a copper-based electrical tape that works as a touch sensor to detect when somebody holds the piece (Figure 1C).

Finally, we equipped the puzzle piece and glove with an ESP-32 microcontroller and the IMU MPU650 capable of logging accelerometer + gyroscope data, i.e., motion data (Figure 1D). The ESP32 processor's technical specifications limited the number of sensors in each glove.

The final version of each glove weighed around 70 grams, costing approximately US$95, while the cost of each puzzle piece was around US$13.

4 Formative Evaluation of the HAR Technology

Considering the concerns informed in [24] about the implications of the hand size in the performance of their one-size fits all gloves, we conducted a user study with 15 children to obtain feedback on the design of the HAR technology. The study consisted of putting on one glove in the dominant hand of the participant who must make three different movements using a piece model (i.e., taking the piece from outside a four-position board and putting it into one specific position into the board) in which we observed how the participant manipulated the piece.

4.1 Methods

The experiment was conducted in a private facility with conditions suitable for the study.

4.1.1 Participants

We recruited 15 children (eight female) and one more child for pilot testing (see Table 1). All children were neurotypical individuals aged 7-13 (Mean age: 9.73; SD=2.016). All mothers signed consent forms on behalf of the underage children. Mothers were absent during the study to avoid children relying on them.

4.1.2 Task Description

Limited by the experimental nature of the glove and the piece where a full puzzle is missing, we studied videos from previous works[22, 23] to identify common piece movements when children play with a puzzle board. From the set of movements, we considered only three of them to avoid a long session time.

The participants performed three tasks, simulating a player moving one puzzle piece from one position to another. A board was drawn on a 42x59 cm white sheet paper (see Figure 2), divided into four sections numbered consecutively from one to four, starting at the top left section. We next describe each task:

- Task 1 (T1): The participant must pick up a piece outside the board and place it on position 1. Then, the participant must pick it up again and place it outside the board to its original position.
- Task 2 (T2): Move the piece from position 1 to position 2, picking it up again and bringing it to position 1 horizontally.
- Task 3 (T3): Move the piece from position 1 to position 3, returning it to position 1, simulating a vertical movement.

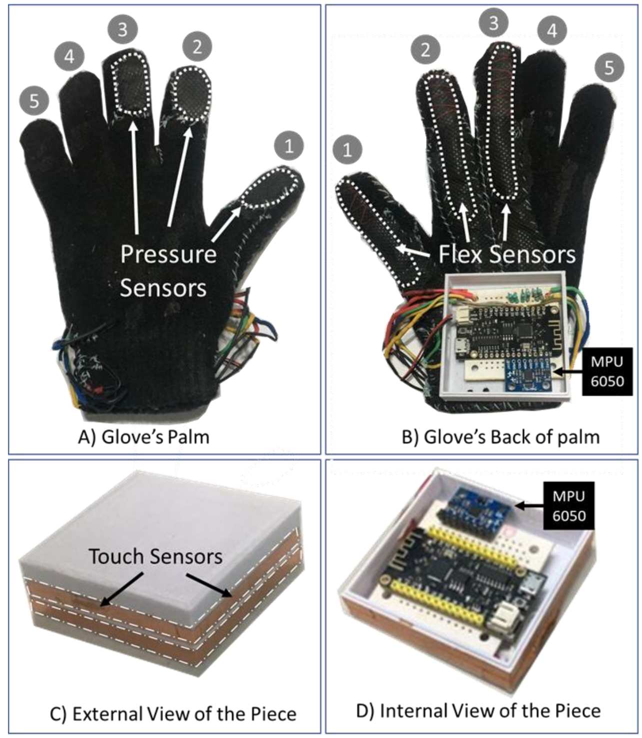


Figure 1. Prototypes of the child's glove and the piece. Dotted lines indicate the location of sensors.

Figure 2. Experimental setting: the board, the piece, and the child wearing the glove.

We asked participants to execute each task ten times (i.e., 30 executions) during each session. The activity finished when the participant completed the three tasks. We did not randomize the task order, considering that all tasks shared similar complexity. Participants received instructions from the research team during the individual sessions.

Table 1. Participants' Demographic

Participant	Gender	Age	Palm size (cm)	Hand large (cm)	Wore gloves before	Dominant hand
P1	F	12	18.5	17.5	No	Right
P2	M	7	16.5	16.0	No	Right
P3	M	8	16.5	15.0	No	Right
P4	F	9	16.5	15.5	No	Right

P5	F	10	17.0	16.7	No	Right
P6	F	13	19.0	18.5	No	Right
P7	M	9	16.0	14.5	No	Right
P8	M	8	15.0	14.5	No	Right
P9	M	12	19.5	17.5	No	Left
P10	M	12	18.5	16.5	No	Right
P11	F	7	15.0	14.5	No	Right
P12	F	8	16.0	15.0	No	Right
P13	M	10	17.7	15.5	No	Right
P14	F	9	15.5	14.0	No	Right
P15	F	12	16.8	16.5	No	Right
	Avg. **Sd**	**9.73** **2.02**	**16.93** **1.42**	**15.85** **1.33**		

4.2 Research Procedure

We carried out the study over three days. The sessions were developed in the same venue. We used two video cameras and one sound recorder during all sessions.

Each child performed the tasks individually, wearing the glove during the session. The average effective time spent by each child solving the three tasks was 03:10 min (Max=4:01 min; Min=2:22 min; SD 0:27 min). Time spent on instructions at the start and between each task is not considered.

Each session was as follows:

- The session started with initial instructions on the calibration task. The participant performed a calibration task to gather the sensor values when she held the piece and when her hand was empty and fully extended. These data constitute reference values to identify a bent finger or a finger touching an object.
- Then, before each task, the participant received verbal instructions on how to perform it. Using the piece, the researcher carefully explained: (a) where to pick up the piece, (b) how to bring it to the corresponding position and release it, (c) when to make a pause, and (d) how to pick up the piece and bring it to its initial position, emphasizing the need to pause before attempting the task again.
- At the end, each participant was thanked for their participation.

Two members of the research team and the participant were present during each session: one leading the sessions and one in charge of the system's performance, including the development of the calibration task and the video recording of each session.

We developed a pilot testing session with one participant. Some adjustments were made to the instructions guide, the calibration task, and the glove design. For instance, we solved short-circuit troubles in the glove by insulating conductive threads that communicate the flex sensors with the CPU onboard. Video cameras and the sound recorder were not relocated. The final physical arrangement of the experiment can be seen in Figure 3.

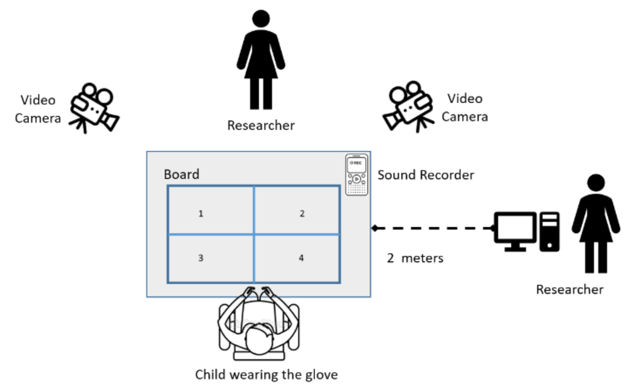


Figure 3.The final physical setting of the experiment.

4.3 Collected Data

Two researchers coded each session video separately (three videos for each session, one for each task, total video length=86:03 min; total audio length=87:03 min).

We coded three events for each finger when the participant was holding the piece: (a) the finger is bent, (b) the finger is touching any part of the piece, and (c) the finger is touching the touch sensors in the piece. The occurrence of every event was classified as Rarely (Coded as 1) if the event seldom happened; Sometimes (Coded as 2) if the event happens about half of the times the child holds the piece; and Frequently (Coded as 3) if the number of times the event occurs is close to the number of times the participant holds the piece.

The coding process worked as follows: First, the two coders worked on the videos separately. When they finished video coding, both coders compared and analyzed the data to identify differences. They then discussed all the differences, agreeing on the final data and codes.

4.4 Data Analysis

For data analysis, we use descriptive and inferential statistics. We investigated the behavior of each finger when the children held the piece (finger bent, finger touching the piece, and finger touching the sensors of the piece) regardless of the task. We used frequency as the primary indicator. We used an ANOVA and a post-hoc Tukey's HSD to validate the media differences in fingers' data.

5 Results

Table 2 shows the data coded from the videos of the three tasks performed by all participants. The data represents the average values of fingers' actions based on the scale defined by the coders.

Values below 2 indicate that participants rarely used their fingers to make the action, and values over 2 indicate that participants commonly used their fingers to make the action.

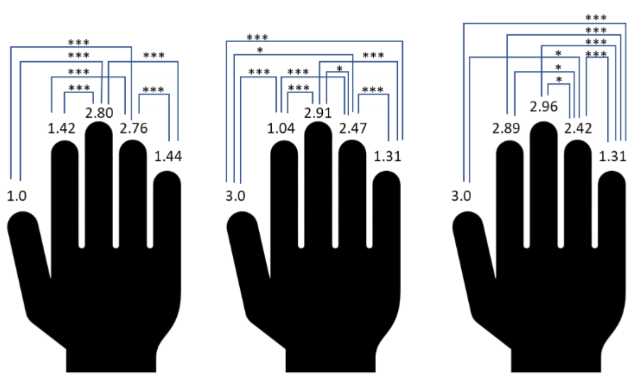
To ease data interpretation, each finger was assigned a number, as shown in Figure 1: thumb (F1), index (F2), middle (F3), ring (F4), and pinky (F5).

Table 2. Media of Data Coded by Task.

		T1		T2		T3	
Action	**Finger**	**Avg.**	**SD**	**Avg.**	**SD**	**Avg.**	**SD**
Finger in touch with the sensors in the piece	F1	3.00	0.00	3.00	0.00	3.00	0.00
	F2	**1.00**	0.00	**1.13**	0.52	**1.00**	0.00
	F3	2.87	0.52	2.87	0.52	3.00	0.00
	F4	2.40	0.91	2.53	0.83	2.47	0.83
	F5	**1.40**	0.83	**1.40**	0.83	**1.13**	0.52
Finger in touch with the piece	F1	3.00	0.00	3.00	0.00	3.00	0.00
	F2	2.80	0.41	2.93	0.26	2.93	0.26
	F3	3.00	0.00	2.87	0.52	3.00	0.00
	F4	2.40	0.91	2.40	0.91	2.47	0.83
	F5	**1.40**	0.83	**1.40**	0.83	**1.13**	0.52
Finger's Flexion	F1	**1.00**	0.00	**1.00**	0.00	**1.00**	0.00
	F2	**1.40**	0.63	**1.53**	0.64	**1.33**	0.49
	F3	2.80	0.41	2.80	0.41	2.80	0.41
	F4	2.87	0.35	2.73	0.59	2.67	0.62
	F5	**1.40**	0.83	**1.53**	0.92	**1.40**	0.83

Coding Scale: Rarely=1; Sometimes=2; Frequently=3.

We used an ANOVA for each action, grouped by finger across all tasks. Significant differences were reported. In Figure 4, we present visually the significant differences between conditions reported by a post-hoc Tukey's HSD.



a) Finger's flexion b) Finger in touch with the sensors of the piece c) Finger in touch with the piece

significance: *** p<0.001 ** p<0.01 * p<0.05

Figure 4. Tukey's HSD significant differences between groups across all tasks. Numbers above each finger represent the finger mean score across tasks T1, T2, and T3.

5.1 Fingers' flexion

Data for fingers F1, F2, and F5 show that children rarely bent their index, thumb, and pinky fingers (mean < 1.884) across all conditions. In contrast, children frequently bent the 3 and 4 fingers when holding the piece.

The ANOVA shows a significant difference between the three conditions: T1(F=41.469, df=74, p < 0.001), T2(F=27.323, df=74, p<0.001), and T3(F=35.058, df=74, p<0.001).

A post-hoc Tukey's HSD shows that fingers F1, F2, and F5 have no significant differences across all conditions, and fingers F3 and F4 show no significant differences. However, fingers F1, F2, and F5 are all significantly different (p<0.001) from F3 and F4 across all conditions.

5.2 Finger in touch with the sensors on the piece

Data for fingers F2 and F5 reflects that they barely were in contact with the touch sensors that wrap the piece for all children across all tasks (mean < 2.146), while data for fingers F1, F3, and F4 shows that children commonly touched the sensors in the piece.

The ANOVA shows a significant difference between the three conditions: T1(F=33.503, df=74, p < 0.001), T2(F=29.114, df=74, p<0.001), and T3(F=75.960, df=74, p<0.001).

A post-hoc Tukey's HSD shows that fingers F2 and F5 have no significant differences across all tasks. No significant differences were found for fingers F1, F3, and F4 for T1 and T2. However, in T3, significant differences (p<0.05) between fingers F1 and F4 and fingers F3 and F4 were found.

5.3 Finger in touch with the piece

Data for fingers F1, F2, F3, and F4 shows that all participants touch the piece with these fingers almost all the time when holding the piece (mean > 2.516), while finger F5 is barely used.

The ANOVA shows a significant difference between the three conditions: T1(F=20.110, df=74, p < 0.001), T2(F=18.168, df=74, p<0.001), and T3(F=46.602, df=74, p<0.001).

A post-hoc Tukey's HSD shows a significant difference (p<0.001) between finger F5 and each of the fingers (i.e., F1, F2, F3, F4) across all conditions. There is a significant difference between finger F4 and fingers F1 and F3 for T1 and between finger F4 and fingers F2 and F3 for T3.

6 Discussion

The flex sensors in the thumb (F1) and index (F2) fingers do not fulfill their function. Most children never bent their thumb and index fingers to grab the piece. In almost all tasks, they left them stretched out at the top of the piece, so the flex data for these two fingers is always close to zero. The middle (F3) finger was the only finger equipped with a flex sensor that behaved as expected. Practically all children bent this finger when holding the piece.

Children frequently used the ring (F4) finger to hold the piece. However, we did not collect essential data because this finger does not have a flex sensor.

Although most children did not bend their F1 and F2 fingers, all three fingers with flex sensors had physical contact with the piece's surface, so the pressure sensors in the fingers collected data as expected.

However, our initial design considered that when a child held a piece, all the pressure sensors in the glove would be in contact with the touch sensors in the piece.

The thumb practically touched the pressure sensor all the time while the children were holding the piece in their hands despite whether it was bent or not, maybe due to its morphology; the middle finger behaved as expected in the three tasks because the children bent this finger almost all times they held the piece. This was different for the index, which practically never touched the pressure sensors surrounding the piece because most of our participants left it stretched out at the top.

This behavior is supported by the researchers' observations, who reported that the children unexpectedly held the piece, using their thumb, middle, and ring fingers instead of their thumb, index, and middle. Figure 5 shows a child holding a piece.

The results indicate that the sensors' location on most of the glove's fingers needs to be improved to collect parent-child interaction data automatically.

The touch sensors are located adequately in the piece if we consider the possibility of changing the sensors in the glove to the fingers that intervene when the children grab the piece.

Figure 5**. A participant is holding a piece in an unexpected way.**

6.1 Revisiting the Glove Design

The results of our formative evaluation imply that flexion data gathered automatically for the thumb and index fingers does not help identify whether the child is holding the piece. Also, the lack of sensors on the ring finger caused a critical loss of data that was useful in describing whether the child was holding the piece.

Consequently, we redesigned the glove. The main changes were the relocation of sensors in the thumb (F1), index (F2), and ring (F4) fingers.

Flex sensors were removed from the thumb (F1) and index (F2) fingers because the children maintained them straight when holding a piece. The touch sensor was kept in place. Sensors in the middle finger were not relocated, and flex and pressure sensors were installed in the ring sensor.

The final glove configuration was set as thumb (pressure), index (pressure), middle (flex, pressure), and ring (flex, pressure). The redesigned glove is shown in Figure 6.

Figure 6. Gloves with flex and touch sensors relocated.

The piece design did not undergo any amendment. As most of our participants held the piece the same way, we expect that the relocation of sensors in the glove is sufficient to gather valuable data to achieve our goals. However, future work must be done to test the glove's functionality.

This work could benefit from a larger sample size. Also, using a different type of glove is desirable. Another limitation is the piece's form factor, which was kept unchanged.

7 Conclusion

In this work, we present the results of a formative evaluation of HAR technology for parent-child interactions. We provide details of the construction of an augmented glove and puzzle piece, which are part of an augmented puzzle aimed at the collecting of parent-child interaction data, based on the requirements informed in [22] and the prototypes specifications described in [13, 24, 29].

After the evaluation, using video coding, we detected a problem related to the location of sensors in some fingers of the child's glove, which prevented the system from obtaining data that could be used for activity recognition. The problem resulted from an unexpected way the child held the piece. This resulted in the redesign of the glove and the relocation of some of the sensors.

The results of this study are significant because they suggest that differences in how children and adults manipulate objects may affect the form and functionality of wearables, such as gloves, which should be considered in the design stage. In this way, this work also contributes to the development of mechanism aimed at the gathering of interaction data in parent-child interaction,

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