Mining Interaction Patterns of Children with and without Communication Disorders in the use of Tablets Apps

Francisco Ortin, Juan Ramón Pérez-Pérez, David Cabielles-Hernández, Miguel Sánchez-Santillán, MPuerto Paule-Ruiz
Computer Science Department
University of Oviedo
c/Federico García Lorca 18, 33007, Oviedo
{ortin, jrpp, uo209910, sanchezsmiguel, paule}@uniovi.es

Abstract. *A communication disorder (CD) is an impairment in the ability to receive, send, process, and comprehend concepts or verbal, nonverbal, and graphic symbol systems. Different research works pursue the early detection of communication disorders, because its treatment at early ages shows significant benefits. In a previous study, we developed two applications for tablet devices that help children in the process of learning the sounds and writing of letters and words. Using the Montessori educational method, our applications showed important benefits, for both children with and without communication disorders, in the learning process of letters, words, and their corresponding sounds. In this article, we use the interaction information produced by our applications in the learning sessions. The purpose of our research is to see if there exist particular interaction patterns of children with and without communication disorders, for the two given applications. We use different data mining techniques and algorithms to process the interaction data generated by 353 children through at least nine sessions. There exist statistically significant differences in 7 of the 36 interaction variables measured. For some sessions of both applications, children with CD made more mistakes than those without CD. The only significant interaction pattern retrieved from the data is that the children with the 12% lowest number of taps over letters (3 taps at most) have CD, fulfilled by 28.1% of the children with CD that used one of our applications. This group of children might be representing children with receptive language disorders.*

Keywords. Communication disorder, interaction pattern, tablet applications, data mining

1 Introduction

Communication disorders (CDs) limit the individual's ability to receive, send, process, and comprehend concepts or verbal, nonverbal, and graphic symbol systems (Collins, 2011). CDs include hearing loss, voice and speech disorders, and, on the most essential level, language disorders. It has been estimated that 5% to 10% of Americans may have communication disorders, costing approximately $154 to $186 billion annually (Ruben, 2000). CDs are associated with an unemployment rate of 41.9%, and the population income with CD is 45% of the income of the non-impaired ones (Ruben, 2000). Likewise, the Bureau of Labor indicates that at least 92% of US employment requires good communication skills (Herman & Abraham, 2000). This shows how, nowadays, CDs represent a substantial public health issue (Ruben, 2000).

The early detection and treatment of CDs have been pursued to provide early intervention, a better quality of life, and inclusion in society. Detection is performed at the earliest stages of life with different educational strategies (Paul, 2016). For example, the First Words Project uses the CSBS Developmental Profile (Wetherby & Prizant, 2002) to detect CDs in children less than 24 months old (Wetherby et al., 2003). Infants are first screened with a brief parent-report checklist, followed up with a more in-depth parent report tool and face-to-face evaluation. The findings support the importance of prelinguistic predictors and the role of the family in the early identification of CDs.

The Montessori educational method for children seeks to develop natural interests and activities rather than use formal teaching methods (Montessori, 2021). Created by the physician Maria Montessori, it emphasizes independence, since children are naturally eager for knowledge and capable of initiating learning in a well-prepared environment. Different applications for mobile devices have been developed to apply the Montessori method through different stages in children's learning process. Such applications cover learning letters and words, recognizing phonemes and word sounds, up to reading and creating phrases and sentences (Jones, 2016; McKenzie, Spence & Nicholas, 2018).

The Montessori method has already been successfully used with people with CDs, including children (Pickering, 2017) and even elders with communication disabilities (Douglas, Brush & Bourgeois, 2018). To support that capability, we developed two tablet applications that, following the Montessori method, were designed to help children in the process of learning the sounds and writing of letters and words (Pérez-Pérez et al., 2021). In a former study, our two applications were successfully used in a school with children between 3 and 5 years old, under the supervision of their teachers but with no intervention (Pérez-Pérez et al., 2021). There were children diagnosed with CD (48.3%) and without CD (51.7%) and, for both cases, our tablet applications represented important benefits in the learning process of letters, words, and their corresponding phonemes and sounds (Pérez-Pérez et al., 2021).

Our software records data about how children interact with the tablets to solve the educational activities proposed by the two tablet applications. Such data might represent valuable information to be mined and analyze whether there are differences in the way children interact with the applications. In particular, we search for (combinations of) variables representing interaction patterns that are present in the recorded data to be mined, and see whether that could be used to identify a child has (no) CD.

Therefore, in this article, we raise the following research question:

Are there interaction patterns capable of identifying children with and without communication disorders (for the two given educational tablet applications)?

To answer the research question, we mine the interaction data produced by our two programs with 6 different data mining techniques, 19 algorithms, and two different use-case scenarios of both tablet applications, utilized by 353 children.

The rest of the article is structured as follows. The next section details related work, while the two tablet applications are briefly described in Section 3. Section 4 presents the methodology of our study, and Section 5 discusses the results. Conclusions are drawn in Section 6.

2 Related Work

Considering the DSM-5 taxonomic and diagnostic manual for mental disorders, there are two main classes of CDs (DSM-5, 2014). Language disorders represent difficulties in learning and using language, mainly caused by issues with vocabulary, grammar, and sentence construction. Language disorders can both be receptive (understanding the language) and expressive (synthesizing language constructions). The second class of CDs is speech sound disorders, when there exist issues with pronunciation and articulation in the native language.

The First Words project is aimed at building an evaluation model for identifying children at risk for CDs (Wetherby et al., 2003). The model is focused on children younger than two years old, because of the significant benefits of early intervention. The First Words project uses the Communication and Symbolic Behavior Scales - Developmental Profile (CSBS DP) to measure prelinguistic communication (Wetherby & Prizant, 2002). First, children are screened with a brief form filled in by the parents. Then, the children have a face-to-face evaluation and a more in-depth parent report. Two studies with 232 and 246 children showed that the First Words project can be used as a prelinguistic predictor, emphasizing the important role of the family in using the method to identify CDs at the early stages of life.

There are different software applications to aid children with CDs. Frutos et al. developed a videogame for children and teenagers to help them in the learning and enhancement of habitual language tasks (Frutos et al., 2011). The game encourages the children to repeat the words pronounced by the system for the shown pictogram. The voice signal of the child is analyzed to check whether the word has been pronounced correctly. The correct pronunciation makes the pictogram be visually stored in a success box. The game ends when all the boxes are filled. Frutos et al. do not present a statistical analysis of the performance of their game in the learning process.

Toki and Page developed a web application for children with language learning and speech articulation problems (Toki & Pange, 2010). The pedagogical model of their application is based on the Nearest Neighbor Learning (NNL) method, where students work in groups formed by themselves and are free to move from one group to another (Toki & Pange, 2006). Their web application is based on pronunciation activities in a talent show game. 12 children between 5 and 6 years old were selected to evaluate the software. The usage of the program showed an average benefit of 7% for speech articulation tasks. For language activities, the performance benefit was 4%.

The Montessori method has been included in different technological systems for distinct learning scenarios. TriPOD is a prototype app for tablets, addressed for educational applications (Di Fuccio, Siano & De Marco, 2017). The app was designed to exploit the psycho-pedagogical practices aimed at focalizing the centrality of the manipulation of real objects in the learning processes. They use different tangible objects, equipped with capacitive pins throughout their different shapes. Those objects are recognized by the software when they placed are onto the tablet surface. Children can play with the system autonomously, without the supervision of a teacher or tutor, following the Montessori method. TriPOD recognizes 24 objects, the Dienes' logic blocks, supporting the implementation of different didactic games. To our knowledge, no study to use TriPOD for learning purposes has been undertaken.

There are some other applications for tablets that have been used with the Montessori method for multi-sensory literacy development intervention (Smith, 2012). Examples of such applications are WordBingo, Montessori Crosswords, and ABC Spelling Magic. The interactivity of the tablets allows children to use their fingers to manipulate the screen, creating an emotional experience and enhancing memory. Educators have realized the effectiveness of these devices, together with the impact on learning, for different intervention programs including dyslexia, dyscalculia, and attention deficit hyperactivity disorder (Drigas & Gkeka, 2017).

3 Tablet Applications

Our two tablet applications deal with reading and writing skills during the first educational stages of children. The first application, Matching Cards, gives a lexical awareness of words. It is not necessary to have previous knowledge of word spelling, since the task is focused on comparing shapes. The second one, Cards & Sounds, develops phonological skills by discovering how words are pronounced, comparing them, and finding out which sound each word begins with. Instructions are given orally by the applications at every step.

The Matching Cards is based on the Picture Exchange Communication System (PECS), using cards with pictograms and written words (Bondy & Frost, 2008). Cards about the same item should be matched by drag and drop actions. Tapping on the cards produces a sound related to the tapped item. Correctly matched cards are grouped, whereas wrong matches produce moving cards to their original position.

The left-hand side of Cards & Sounds shows boxes with all the letters, which play the corresponding phoneme when they are tapped. Four images (pictograms) appear on the right-hand side of the screen (they are also pronounced when tapped). The child should drag each image and drop it over the corresponding letter. When a letter is matched, its background color becomes gray and the card disappears to indicate that the action is correct; otherwise, the drag-and-drop action is revoked.

The interaction data stored by both applications are:

- `TotalTime` (real number). How long it took the child to solve the activity, expressed in minutes.
- `AverageTime` (real number). The average number of seconds measured between each interaction (tap or drag and drop action) of the child with the application.
- `Taps` (integer number). Number of taps performed by the student in each session. For Matching Cards, it is just one variable; but two variables are captured for Cards & Sounds:
  - `LetterTaps` (integer number): Number of taps on letters.
  - `WordTaps` (integer number): Number of taps on words.
- `DragDrops` (integer number): Number of drag and drop actions undertaken by the children during the session.
- `Mistakes` (integer number): Number of wrong matches performed by the student during the session.
- `ConsecutiveMistakes` (integer number): The greatest number of consecutive mistakes performed by the child during the session.

Each session requires the child to match the items (two for Matching Cards and four for Cards & Sounds) of four different panels. The data stored is anonymous so no personally identifiable information can be obtained. For a more detailed description of both applications, please consult (Pérez-Pérez et al., 2021) and (Cabielles, 2021).

4 Methodology

4.1 Context

We contacted Montessori associations and public schools in the north of Spain, where nursery education is addressed to children between 3 and 5 years old with and without CD. The children with CD included in our study had been previously diagnosed with language disorder and speech sound disorder. The diagnosis is supplied by the schools and is based on DSM-5 (DSM-5, 2014). Caregivers were responsible for installing the specific activities for the children and, for such purpose, they gave explicit consent. All the caregivers and teachers involved in the study were delivered a face-to-face seminar about how to use the applications and avoid adult intervention during sessions.

The number of children who participated in our study, together with their ages and genders, are depicted in Table 1. In total, 166 children participated in Matching Cards (48.8%/51.2% with/without CD and 45.2%/54.8% males/females) and 186 in Cards & Sounds (47.8%/52.2% with/without CD and 46.8%/53.2% males/females). The average age of students was 5.38 (standard distribution of 1.24).

Table 1. Number (N), arithmetic mean and standard deviation (SD) of ages, and genders of the children who participated in our study.

	Matching Cards		Cards & Sounds	
	Children with CD	Without CD	Children with CD	Without CD
N	81	85	89	97
Age mean	5.5	5.4	5.3	5.4
Age SD	1.2	1.1	1.3	1.2
Males	43	39	43	44
Females	38	46	46	53

4.2 Sessions

The study took place in the first trimester of the academic course. The two case studies (Matching Cards and Cards & Sounds) were carried out in 12 sessions (one session per week). The maximum duration of each session was 15 minutes. As mentioned, each session consisted in matching the items of four different panels. Each child worked independently. No interaction existed among children or between children and teachers or caretakers, following the Montessori method.

Since children of that age often get ill, we considered those who at least attended 75% of the sessions (i.e., 9 sessions out of 12). We considered the data gathered by our two applications in both the first and the last sessions. The purpose is to extract the interaction patterns for the first contact with the learning activity (no former interaction with the application) and once they have experience with the program. This is because differences between children with and without CD might exist in one scenario but not in the other one.

4.3 Data Mining

We mined the four datasets gathered from the log information produced by the two applications for the first and last sessions. We used the following data mining techniques.

4.3.1 Anomaly detection

Anomaly or outlier detection aims to identify unusual data records that may be interesting to analyze. If all the records with anomalous values for a given variable (do not) have CD, that would provide valuable information regarding our research question. Anomalous records may also be caused by measurement errors and, in that case, they should be removed.

For univariate outlier detection, we used Tukey's fences, which is a non-parametric, robust and widespread method to detect outliers. With Tukey's fences, an outlier is defined as an instance that does not belong to the following interval, where Q_n represents the n quartile:

$$[Q_1 - 3\times(Q_3 - Q_1),\ Q_3 + 3\times(Q_3 - Q_1)] \quad (1)$$

For multivariate anomaly detection, we used the isolation forest algorithm that identifies outliers by considering how far a data point is from the rest of the data. We selected this algorithm because it has been measured to provide better performance than other methods such as ORCA, LOF and Random Forests (Liu, Ting & Zhou, 2008).

The contamination hyperparameter specifies the proportion of outliers in the dataset. We found 1% (0.01) as the contamination value that identified outliers in our datasets the best.

4.3.2 Decision tree classification

Decision tree learning is a supervised learning technique to predict values from previous observations. Decision trees are used to foresee one target value from the known features of a given sample. When the values to predict are discrete, decision trees act as classifiers; for continuous values, they become regressors.

A good characteristic of decision trees is that they are easy to understand and interpret. That is why they are useful for both machine learning and data mining. For example, the decision tree in Figure 1, which classifies children after the first interaction with Cards & Sounds, can be used to analyze that dataset. The children who tapped three or fewer times on a letter are diagnosed with CD. 25 out of 186 children fulfilled this condition (13.4%). If `LetterTaps` is greater than 3, other conditions should be checked to know whether the child has a CD. Each path from the root node to a leaf (i.e., a tree branch) represents a classification rule.

An important hyperparameter in decision trees is the maximum depth of the tree (the tree in Figure 1 has a max depth of 3). For deep trees, the predictive model overfits since one branch per sample could be created. Such over-complex models do not generalize well for the training data, and hence they do not produce valuable information. For this reason, we created decision trees with maximum depths from 2 to 10 and analyzed all the trees obtained (see Section 4). Classification rules are then extracted and analyzed to see if they represent an interaction pattern to identify children with(out) CD. We used the CART algorithm to build the decision trees because it supports numeric features and tree pruning as a regularization mechanism.

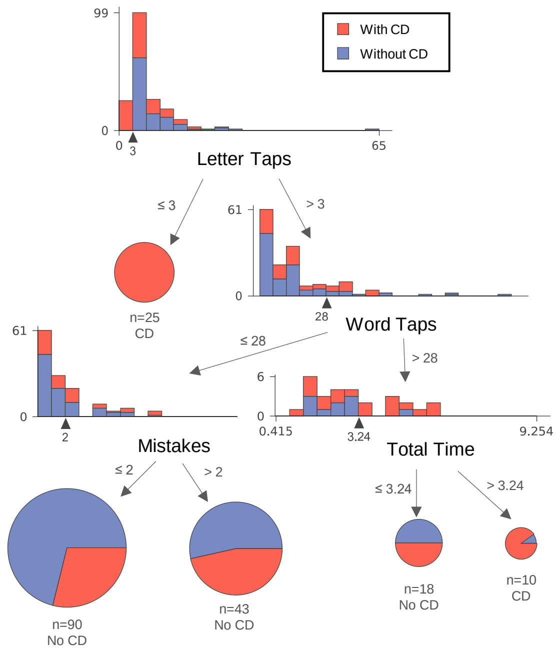

Figure 1. Decision tree for the first session of Cards & Sounds (max depth = 3).

4.3.3 Classification rules induction

Rule induction is a technique in which formal rules are obtained from a set of observations. They can be used to create predictive models (machine learning) and to represent data patterns (data mining). A classification rule is a collection of propositional predicates for a given value of the target feature. For example, the following predicates are used to classify children with CD in the first session of Cards & Sounds:

$\texttt{LetterTaps} \leq 1 \lor (\texttt{Mistakes} \geq 7 \land \texttt{WordTaps} \geq 32)$

The previous rule[1] states that, if a child performs one or no letter taps, or they have more than 7 mistakes and more than 31 word taps, then they have a CD; otherwise, the child has no CD.

There exist different algorithms for classification rule induction. We used the RIPPER*k* and IREP algorithms. The former usually obtains error rates lower than the C4.5 algorithm, scales nearly linear to the number of training instances, and is able to efficiently process noisy datasets (Cohen, 1995). The latter includes an incremental reduced error pruning process that avoids overfitting with noisy data and provides good generalizations (Fürnkranz & Widmer, 1994).

4.3.4 Association rules learning

Association rule learning is a method to discover relations between variables in existing datasets. Let $I=\{i_1, i_2, \dots i_n\}$, be a set of n binary features, then an association rule is defined as:

$$X \Rightarrow Y \quad where\ X, Y \subseteq I \quad and \quad X \cap Y = \emptyset \qquad (2)$$

One important requirement of the i_n features in the dataset is that they must be binary. To meet this prerequisite, we discretized the numeric features into five intervals, following a quantile strategy to define the widths of the bins. In this way, each numeric feature is converted into one of the following five: very low (first quintile), low, average, high, and very high (last quintile). With this discretization, the following example rule was extracted from the last session of our Matching Cards dataset:

$$\texttt{Mistakes} = VeryLow \land \texttt{CD} = False \Rightarrow \texttt{ConsecutiveMistakes} = VeryLow$$

It tells us that, when children have very low mistakes (within the 25th percentile) and they do not have been diagnosed with CD, the number of consecutive mistakes is also very low. This shows how association rules can be used to find interaction patterns that could provide information to answer our research question.

[1] The rule consists of the mentioned predicates as the antecedent and "CD = *True*" as the consequent.

Support and confidence are two widespread metrics to measure the performance of association rules. They are defined as:

$$Support(X \Rightarrow Y) = \frac{number\ of\ instances\ containing\ X\ and\ Y}{total\ number\ of\ instances} \qquad (3)$$

a

$$Confidence(X \Rightarrow Y) = \frac{number\ of\ instances\ containing\ X\ and\ Y}{number\ of\ instances\ containing\ X} \qquad (4)$$

The previous example rule has 28.9% support and 100% confidence.

For our purpose of finding interaction patterns of children with and without CD, we only analyze the association rules with the following criteria. They should have a minimum support threshold of 5% to be considered as representative rules, and at least 90% confidence to tolerate some noise in data. Rules must have the CD binary attribute as the only consequent, since we want to find different patterns for children with and without CD. We used the FP-Growth (Frequent Pattern Growth) algorithm instead of the traditional and widespread Apriori method, because FP-Growth efficiently represents the item sets as a tree of frequent patterns, reducing execution time and memory consumption (Han, Kamber & Pei, 2012).

4.3.5 Dimensionality reduction

Dimensionality reduction is the transformation of data from a high-dimensional space into a low-dimensional one, retaining meaningful properties of the original data. The four datasets used in our study have six and seven dimensions (Section 3). By applying dimensionality reduction techniques, the high-dimensional datasets can be embedded in a low-dimensional space for visualization. In those visualizations, points represent instances (children in our study) in such a way that similar instances are modeled by nearby points and dissimilar instances are represented by distant ones. By plotting children with and without CD with different colors, it is possible to visually identify different patterns for the two groups. Visual groups (clusters) made up of close points with the same color mean that there exists an interaction pattern associated with CD or the absence of it (our research question).

We used eight different algorithms: Principal Component Analysis (PCA), Non-Negative Matrix Factorization (NMF), Factor Analysis (FA), Sparse PCA, Truncated Singular Value Decomposition (SVD), t-distributed Stochastic Neighbor Embedding (t-SNE), Fast Independent Component Analysis (FastICA), and Kernel PCA. The first five algorithms are linear and the three last ones are nonlinear, thereby covering a wide set of alternatives for dimensionality

Table 2. Number of instances (N), arithmetic means, standard deviations (SD), and min and max values of the four datasets (bold font represents variables with significant differences between children with and without CD).

			With CD (N=81)			Without CD (N=82)		
			Mean	SD	Range	Mean	SD	Range
Matching Cards	First Session	TotalTime	1.55	1.10	[0.43 – 7.37]	1.40	0.86	[0.45 – 6.75]
		AverageTime	2.41	1.75	[0.77 – 13.81]	2.22	1.40	[0.77 – 11.91]
		Taps	39.49	7.68	[32 – 78]	38.99	7.05	[32 – 76]
		DragDrops	20.57	6.00	[15 – 51]	19.82	5.02	][15 – 46]
		Mistakes	1.93	2.39	[0 – 11]	2.16	2.40	[0 – 13]
		ConsecutiveMistakes	0.99	1.23	[0 – 8]	1.16	1.04	[0 – 6]
	Last Session	TotalTime	1.16	0.71	[0.45 – 4.84]	1.33	1.21	[0.42 – 7.69]
		AverageTime	1.86	1.03	[0.64 – 6.29]	2.14	1.66	[0.75 – 11.18]
		Taps	38.07	5.80	[32 – 59]	37.26	7.06	[32 – 87]
		DragDrops	18.95	4.22	[15 – 38]	18.79	6.34	[15 – 68]
		Mistakes	**2.12**	**2.16**	**[0 – 8]**	**1.47**	**1.52**	**[0 – 8]**
		ConsecutiveMistakes	1.15	1.15	[0 – 7]	0.86	0.80	[0 – 3]
			With CD (N=89)			Without CD (N=97)		
			Mean	SD	Range	Mean	SD	Range
Cards & Sounds	First Session	TotalTime	1.88	1.55	[0.41 – 9.25]	1.55	0.99	[0.47 – 5.92]
		AverageTime	2.25	1.74	[0.53 – 11.81]	2.00	1.08	[0.71 – 6.84]
		LetterTaps	**5.61**	**5.00**	**[0 – 25]**	**7.96**	**7.69**	**[4 – 65]**
		WordTaps	**24.44**	**8.91**	**[16 – 63]**	**21.02**	**5.93**	**[16 – 51]**
		DragDrops	49.52	13.53	[33 – 103]	46.48	12.19	[36 – 116]
		Mistakes	**3.47**	**3.54**	**[0 – 14]**	**1.51**	**2.38**	**[0 – 11]**
		ConsecutiveMistakes	**1.49**	**1.53**	**[0 – 7]**	**0.89**	**1.22**	**[0 – 6]**
	Last Session	TotalTime	1.30	1.44	[0.41 – 11.78]	0.97	0.71	[0.41 – 4.09]
		AverageTime	1.79	2.14	[0.57 – 18.13]	1.33	0.77	[0.55 – 5.58]
		LetterTaps	**4.57**	**4.15**	**[0 – 25]**	**5.82**	**3.79**	**[4 – 31]**
		WordTaps	**21.55**	**5.78**	**[16 – 46]**	**19.67**	**5.58**	**[16 – 48]**
		DragDrops	44.89	9.44	[34 – 81]	43.02	10.68	[36–103]
		Mistakes	**2.76**	**3.38**	**[0 – 15]**	**1.53**	**2.50**	**[0 – 13]**
		ConsecutiveMistakes	1.12	1.06	[0 – 5]	0.98	1.51	[0 – 9]

reduction. We reduce the datasets to two-dimensional data, and the resulting data are visualized to graphically analyze the existence of different patterns related to CD.

4.3.6 Clustering

We also apply clustering algorithms to detect groups of children (clusters) that show similar interaction patterns. Clustering algorithms are unsupervised machine learning techniques that find similar groups of instances from unlabeled datasets. We automatically gather the clusters of children from the datasets of our study (suppressing the CD variable). Then, we check whether any cluster is made up of children with or without CD. In such a case, the cluster represents an interaction pattern of children with or without CD. If so, we analyze the features of the cluster to document the interaction pattern associated with or without CD.

Most clustering algorithms are sensitive to outliers. Thus, once outliers are detected and documented (Section 4.3.1), we do not include them in the dataset passed to the clustering algorithm. We also perform a z-score normalization of the data before running the clustering algorithms, because that commonly improves the efficiency of the algorithms.

We ran the following clustering algorithms due to their good performance and the variety of approaches they represent (Berkhin, 2006): k-means, spectral clustering, DBSCAN (Density-Based Spatial Clustering of Applications with Noise), agglomerative clustering, and OPTICS (Ordering Points To Identify the Clustering Structure). For those algorithms that require us to specify the number of clusters, we executed them with 2 to 10 clusters. Out of the clusters found, we analyze those with at least 10 children where 90% of them either have (or do not have) CD.

5 Results and Discussion

Table 2 shows the arithmetic means, standard deviations, and maximum and minimum values of the features of the four datasets. We used the unpaired student's *t*-test and Wilcoxon statistical hypothesis tests to see if there are significant differences between children with and without CD. Rows in bold font in Table 2 indicate that, for that feature, the null hypothesis (means of two populations are equal) can be rejected (p-value<0.05).

For Match & Cards, the number of mistakes in the final session is the only feature that shows significant differences. Children with CD show more mistakes than children without CD in the last session. That could imply that, after practicing, children without CD are

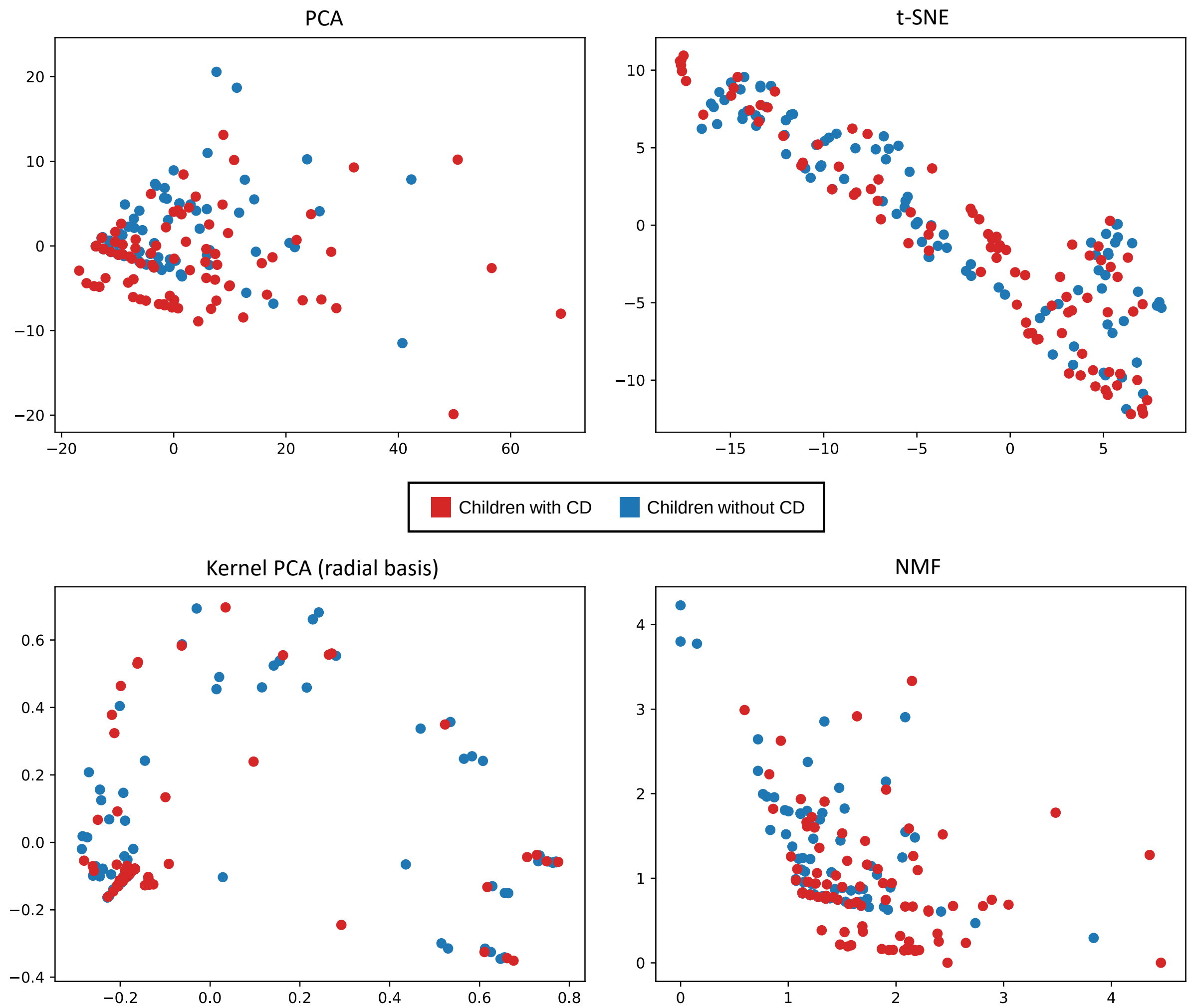

Figure 2. PCA, t-SNE, Kernel PCA (radial basis function), and NMF visualization of the first session of Cards & Sounds.

able to solve the activity with fewer mistakes than those with CD.

In Cards & Sounds, mistakes are significantly different in both sessions, and children with CD have significantly higher values. The same occurs for the consecutive mistakes, but only for the first session. Therefore, after practicing, children with CD no longer show higher consecutive mistakes than children without CD.

Letter and word taps also show significant differences for both the first and last sessions of Cards & Sounds. For word taps, children with CD require, on average, more taps than those without CD. It is the opposite for letter taps.

A feature with significantly different values indicates that the means of the two groups are not the same, but it does not necessarily mean that that feature can be used to successfully identify whether a child has been diagnosed with CD (our research question). Hence, we apply different data mining algorithms to see if those significant differences represent sufficient dissimilarity to find interaction patterns that identify children with or without CD.

5.1 Anomaly Detection

We used the outlier detection algorithms described in Section 4.3.1. For the Matching Cards dataset, three outliers were found. One child with CD that, for the first and last session, showed very high `TotalTime`, `Taps`, and `Mistakes`. Another one with CD presented, in the last session, very high values of `TotalTime`, `Taps`, and `DragDrops`. The third outlier had no CD, and also showed high `Taps`, `DragDrops`, and `Mistakes`. Therefore, regarding our research question, it cannot be stated that outliers with high values of any feature are associated with (no) CD.

For the Cards & Sounds application, we have similar results. Five outliers were found, three for the first session and two for the last one. All of them have very high values for at least two features. There are outliers with and without CD in both sessions, so we cannot conclude that atypical feature values are associated with (no) CD diagnosis (our research question).

Table 3. Association rules found (both obtained from the Cards & Sounds application).

Rule	Confidence	Support	Session
`LetterTaps` = *Very Low* ∧ `Mistakes` = *Average* ∧ `WordTaps` = *High* ⇒ `CD` = *True*	100%	5.4%	First
`Mistakes` = *Low* ∧ `ConsecutiveMistakes` = *Very Low* ⇒ `CD` = *True*	100%	5.4%	Last

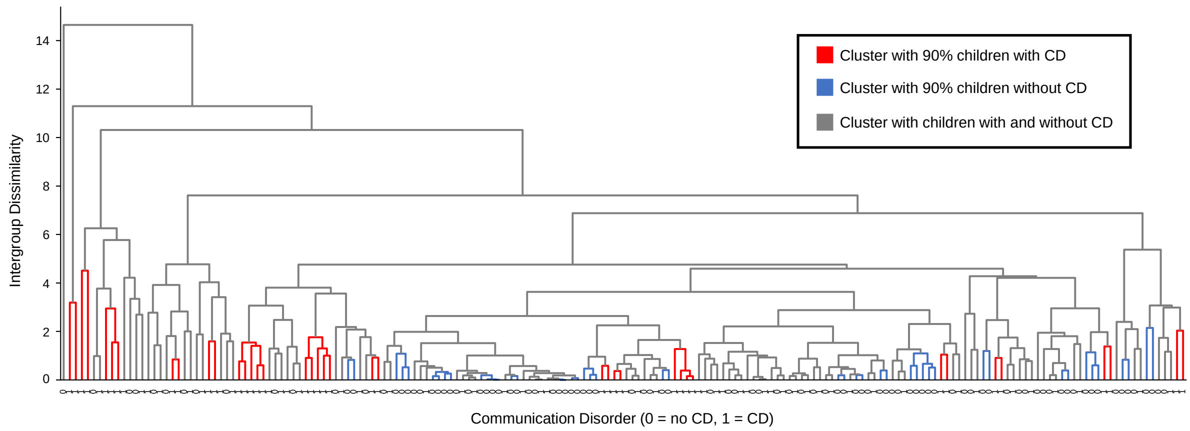

Figure 3. Dendrogram showing the agglomerative clustering for the last session of Cards & Sounds.

5.2 Decision Tree Classification

We created decision trees for the four datasets, with maximum depths from 2 to 10 (40 decision trees in total). Then, we analyzed the classification rules (tree branches) in those trees that at least classify 10% of the population with a minimum accuracy (correct classifications) of 90%. Only one single rule, retrieved from the Cards & Sounds trees (both sessions), met these criteria (one of such trees can be seen in Figure 1).

The classification rule found for both sessions was "`LetterTaps` ≤ 3 ⇒ `CD` = *True*". It has 100% accuracy and classifies 13.4% (first session) and 12.4% (last session) of all the children. Thus, the "`LetterTaps` ≤ 3" condition is only met by children with CD in the Cards & Sounds application, both in their first interaction and after at least nine sessions. Concerning our research question, this is the only interaction pattern extracted from the decision trees built.

5.3 Classification Rules Induction

The RIPPER*k* and IREP algorithms obtained 16 classification rules. The classification accuracies obtained ranged from 50.6% to 70.4% (average 60.9%). These classification accuracies are very low, considering that we have a binary classification problem (i.e., 50% accuracy is obtained by a random classifier).

The antecedent of each classification rule is expressed as disjunctions of conjunctions of propositional predicates $((p_{11} \lor \ldots \lor p_{1n}) \land \ldots \land (p_{m1} \lor \ldots \lor p_{mn}))$, where the consequent is one value of the `CD` target variable. Therefore, each disjunction may be interpreted as a pattern or subrule aimed at classifying part of the population (e.g., $p_{11} \lor \ldots \lor p_{1n} \Rightarrow$ `CD` = *True*). We analyzed all the subrules, selecting those with a minimum accuracy of 90%.

The only rule meeting the 90% accuracy criterion was "`LetterTaps` ≤ 1 ⇒ `CD` = *True*", for the two sessions of Sounds & Cards (100% accuracy and 11.8% and 11.3% support). This rule is a subrule of the one found with decision trees (Section 5.2), so a new interaction pattern is not found.

5.4 Association Rules Learning

We ran the FP-Growth algorithm against our four datasets, obtaining 3,852 association rules. To gather the patterns asked in our research question, we then filtered those rules with a minimum accuracy of 90% and 5% support, having CD as their unique consequent.

Table 3 shows the two rules found, both for the Cards & Sounds application. Both define a pattern for children with CD, with 100% accuracy but representing only 5.4% of the children. As with the previous rules, the first rule in Table 3 keeps identifying a very low number of letter taps, combining it with average mistakes and a high number of word taps, but with much lower support (5.4%).

The second rule associates low and very low number of mistakes and consecutive mistakes to children with CD, after using the application in all the sessions. However, this result cannot be generalized to "children with CD have fewer mistakes" because of the following reasons:

a) There are no significant differences in the `ConsecutiveMistakes` variable (Table 2).
b) Significant differences exist for `Mistakes`, but the mean of children with CD is higher than those without CD.

c) The association rule just represents 5.4% of the children.

Therefore, the association rules extracted do not represent a sufficiently significant interaction pattern to identify children with or without CD.

5.5 Dimensionality Reduction

We reduced the dimensions of the four datasets to two, using the eight algorithms described in Section 4.3.5. The explained variances with two dimensions for the PCA algorithm ranged from 94.3% to 95.4%. This means that the distribution / visualization of the data in two dimensions only loses around 5% of the variability of data, so little information is dropped.

Figure 2 visualizes the first session of Cards & Sounds, using the PCA, t-SNE, Kernel PCA (radial basis as the kernel function), and NMF algorithms. In the representations, we cannot clearly identify a group of points (clusters), close among them, distant from the rest of the points, and with a substantial number of instances. Kernel PCA is probably the visualization that groups more instances (children) together (e.g., points around x=0.7 and y=-0-1). However, no cluster holds children only with or without CD (i.e., points with the same color). After analyzing all the plots, we did not identify a group of children (points) with or without CD (similar color) representing a similar interaction pattern.

5.6 Clustering

By running the five different clustering algorithms described in Section 4.3.6, we obtained 506 clusters of different sizes that represent distinct interaction patterns. Then, we considered those clusters whose instances account for at least 90% of children either with or without CD. All the clusters meeting that requirement hold at most 10 children, representing only 5.38% of the population. The only cluster with 10 children is the already discussed interaction pattern for the Cards & Sounds activity, where the value of `LetterTaps` is very low.

The disassociation between the clusters found and the CD diagnosis classification can be seen in Figure 3. That figure hierarchically displays agglomerative clusters from one single child (bottom of the figure), comprising them up to one single cluster with all the children (top of the figure). The height of clusters is proportional to the value of the intergroup dissimilarity. Red and blue colors indicate clusters with at least 90% of the children with and without CD, respectively. Gray color indicates mixed values. It can be seen how only clusters with at most five children have 90% of their instances with the same CD value. Responding to our research question, the clustering algorithms utilized found no representative interaction patterns to identify children with or without CD.

6 Conclusions

In a previous study, we showed how two tablet applications, which follow the Montessori method, can help children with and without CD in the process of learning the sounds and writing of letters and words. In this article, we study whether, using those two applications, it could be found interaction patterns capable of identifying children with and without communication disorders. The only significant pattern found, followed by 12.4% of the children in the Cards & Sounds activity, is that the children with the 12% lowest number of taps over letters (3 taps at most) have CD. This is fulfilled for both the first interaction with the application and the last one, after at least eight sessions of training. The pattern is also supported by the significant difference in the variable that measures the number of taps on letters, where children with CD show lower values than children without CD. The pattern may be representing the fact that some of the children with CD do not find it useful to hear the starting phoneme of one word to match it with the corresponding word, due to their CD. According to the DSM-5 classification of CDs, the interaction pattern found might be representing some of the children with receptive language disorders, since hearing the starting phonemes does not help in solving the activity. CDs include a wide range of diagnosis categories and the pattern found is only followed by 28.1% of the children with CD involved in the study.

All the datasets used in our study, the source code implemented to mine all the information, and the data mining models created are freely available for download at https://reflection.uniovi.es/download/2022/com-dis/

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