

ChildCI framework: Analysis of motor and cognitive development in children-computer interaction for age detection

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ABSTRACT

This article presents a comprehensive analysis of the different tests proposed in the recent ChildCI framework,¹ proving its potential for generating a better understanding of children's neuromotor and cognitive development along time, as well as their possible application in other research areas such as e-Health and e-Learning. In particular, we propose a set of over 100 global features related to motor and cognitive aspects of the children interaction with mobile devices, some of them collected and adapted from the literature.

Furthermore, we analyse the robustness and discriminative power of the proposed feature set including experimental results for the task of children age group detection based on their motor and cognitive behaviours. Two different scenarios are considered in this study: (i) single-test scenario, and (ii) multiple-test scenario. Results over 93% accuracy are achieved using the publicly available ChildCIdb_v1 database (over 400 children from 18 months to 8 years old), proving the high correlation of children's age with the way they interact with mobile devices.

1. Introduction

Technology has become a very important aspect of our lives in recent decades. In particular, mobile devices play an essential role in our daily basis (e.g., work, relationships, communications, business, etc.). This also affects children, who are exposed to these devices from an early age (Antle & Hourcade, 2021). Recent studies corroborate this fact (Kabali et al., 2015; Kılıç et al., 2019). For example, Kabali et al. (2015) conducted a study with 350 children aged 6 months to 4 years concluding that 96.6% of children use mobile devices, and most started using them before the age of 1 year. In addition, around 75% of children by the age of 4 years already have their own mobile device. Similar conclusions were obtained in Kılıç et al. (2019), where 422 parents of children aged from birth to 5 years were interviewed and 75.6% of them indicated that their children had already used mobile devices at that age. Moreover, and due to the global pandemic of COVID-19 since 2020, the use of mobile devices has been rapidly increased as preschools, kindergartens, and schools were closed down for several months in most countries around the world. As a result, traditional

face-to-face education was replaced to virtual learning environments (e-Learning) (Antle & Frauenberger, 2020).

Despite the high technological evolution and the application of it in children scenarios, the assessment of the correct motor and cognitive development of children is still evaluated using traditional approaches that are manual, time-consuming, and provide qualitative results that are difficult to interpret. This is one of the main motivations of our ChildCI framework (Tolosana, Ruiz-Garcia et al., 2022): the proposal of automatic methods that quantify the motor and cognitive development of the children through the interaction with mobile devices, using both the stylus and the finger/touch. As a first step towards that future goal, in this article we first evaluate the discriminative power of the tests proposed in the ChildCI framework, trying to shed some light on the following questions: Is there any relationship between children's chronological age and their motor and cognitive development when interacting with the tests proposed in ChildCI framework? Is there any relationship between the age, the type of test, and writing input (stylus/finger) considered? The answers to these questions could provide very interesting insights for the research community and the proposal

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¹ https://github.com/BiDALab/ChildCIdb_v1.

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of automatic and usable methods to better quantify the development of the children.

The main contributions of the present work are:

- An in-depth revision of recent works studying children's interactions on mobile devices (using both finger and stylus), as well as the analysis of motor and cognitive development.
- Validate the potential of the different tests included in the ChildCI framework in terms of the motor and cognitive development of the children. We propose a feature set with over 100 global features based on cognitive and motor aspects of children while interacting with mobile devices, some of them collected and adapted from the literature.
- Analyse whether there is any relationship between the chronological age of the children and their motor and cognitive development while interacting with the tests included in ChildCI. To shed some light on this, experiments are carried out for the task of children age group detection based on their motor and cognitive behaviours. Three groups are considered: 1 to 3 years, 3 to 6 years, and 6 to 8 years. Different acquisition inputs are considered in the analysis, i.e., stylus and finger. In addition, single- and multiple-test experiments are studied. Experiments are performed including several automatic feature selection techniques and machine learning approaches.

The remainder of the article is organized as follows. Section 2 summarizes previous studies on children's touch and stylus interaction, as well as some sets of features successfully used in literature for different lines of work. In the following, we describe in Section 3 the ChildCI framework and database used in the experimental work carried out. Section 4 describes the proposed feature set based on motor and cognitive aspects of the children. Section 5 describes the experimental protocol and the results achieved for the task of children age group detection. Finally, Section 6 draws the final conclusions and future work.

2. Related works

2.1. Children interaction: Stylus vs. Finger

From such an early age and throughout their development, children experience different evolutionary stages in which their physiological and cognitive capacities improve through continuous interaction with the world they live. Piaget and Inhelder were the leaders of the study of children's motor and cognitive development and, according to their theory (Piaget & Inhelder, 2008), children pass in a fixed sequence through four universal stages of development: (i) *Sensorimotor* (from birth to 2 years), children focus on acquiring knowledge by using their senses to touch, smell, see, taste, and hear the objects around them; (ii) *Preoperational* (2–7 years), their language and thinking improve together with their motor skills. In addition, at this age children are egocentric in their thinking and it is still difficult for them to empathize with other people's feelings; (iii) *Concrete Operational* (7–11 years), children begin to use more logical thinking to solve problems, starting to improve their empathic abilities significantly; and (iv) *Formal Operational* (11 years to adulthood), they gain the ability to use abstract cognitive functions to think more about moral, philosophical, ethical, social, and political issues.

Children's interaction with mobile devices has been evaluated and analysed by multiple research studies in recent decades. Focusing on the first stage of Piaget's theory (Sensorimotor, 0–2 years) there is not much work on the interaction analysis of children under the age of 2 with touchscreen devices, mainly due to the difficulty of capturing data with children at that age. If we focus on touch mobile interactions, Morante, Costa, and Rodríguez (2016) presented a very interesting article in this line. In that work, the authors analysed the

behaviours of children aged from 0 to 2 years. They concluded that children at 1 year of age can use the tap gesture intentionally to perform actions and at 2 years they are already able to understand some gestures such as tap and drag to navigate through apps. Hourcade, Mascher, Wu, and Pantoja (2015) assessed the mobile interaction of children aged 1 to 2 years through the analysis of videos from YouTube while they were recorded interacting with mobile devices. They concluded that children under 17 months tend to use both hands for interaction, an aspect that decreases sharply with age, leading to single-hand use.

Looking at the second stage of Piaget's theory (Preoperational, 2–7 years), several studies have analysed the children's interaction with mobile devices, in contrast with the first stage. For example, in the work presented by Vataavu, Cramariuc and Schipor (2015), a database of 89 children aged 3 to 6 years and 30 young adults was presented. This database was also considered in the experimental protocol of Vera-Rodríguez et al. (2020). In that work, classification rates above 96% were achieved for the adult-child detection task using an automatic system based on neuromotor skills. A similar research line was studied in Nacher, Jaen, Navarro, Catala, and González (2015) where the authors proposed a set of 8 different tests on a mobile device in order to measure the ability of children aged 2–3 years to perform touch gestures. The results showed that simple gestures such as tap, drag, and one-finger rotation can be performed by children in most cases. However, performing more complex gestures such as double tap, scale down, long press, and two-finger rotation is strongly influenced by the age of the child, with the older children's group performing them easier and quicker than the younger ones. Similar conclusions were obtained by Chen et al. (2020). The authors found different children's interaction behaviours with mobile devices by analysing the correlation between factors such as their age, grade level, motor and cognitive development, and how they performed touchscreen interaction tasks (target acquisition and gesture detection).

Interaction with mobile devices is not only done through the use of the finger, but also through an stylus (Tolosana et al., 2021, 2022). In general, writing and drawing require greater motor and cognitive development than simple touch gestures. Children start scribbling around the age of 2 years (Price, Jewitt, & Crescenzi, 2015). Rémi, Vaillant, Plamondon, Prevost, and Duval (2015) studied the way children aged 3–6 years perform scribbling activities, concluding that there are significant differences in motor skills depending on the age. Another interesting work in this line is presented in Tabatabaey-Mashadi, Sudirman, Guest, and Khalid (2015) considering children 6–7 years old. The authors analysed the correlation between the performance of polygonal shape drawing and levels in handwriting performance. The results proved that there are different children's drawing strategies that differ in their writing performance.

2.2. Motor and cognitive development

The way certain actions and gestures are performed on a touchscreen device determines the behavioural patterns associated with a specific individual (Schadenberg, Neerincx, Cnossen, & Looije, 2017; Singh, Kumar Singh Kushwaha, Chandni, & Srivastava, 2023). In particular, the correct analysis and quantification of the motor and cognitive development of the children is based on a good definition of robust and discriminative features for the task. Previous studies in the field of Human–Computer Interaction (HCI) could provide interesting features that, after adapting them, could be very useful to analyse motor and cognitive aspects of the children.

For example, Ishii, Mochizuki, Shiomi, Nakazato, and Mochizuki (2020) developed a simple quantitative method to diagnose tremor using hand-drawn spirals and artificial intelligence. The Archimedes spiral is the reference test for the clinical diagnosis of diseases such as essential tremor or Parkinson. In that study, patients used a stylus to trace a spiral on a printed reference spiral and, by comparing the lengths of the reference spiral and the traced one, the total area of

deviation between both was calculated, achieving results with success rates up to 79% in detecting people with essential tremor. In a similar work, Solé-Casals et al. (2019) proposed a new set of 34 features using only the x and y coordinate points of the strokes made by patients as they traced the Archimedes spiral using a pen stylus on a graphics tablet. In addition to tremor assessment, Lin, Chen, Yang, and Chen (2018) proposed a test paradigm on a graphic tablet using different parameters to automatically quantify tremor characteristics and severity in real-time by extracting three parameters: (i) the mean radial difference per radian, (ii) the mean radial difference per second, and (iii) the area under the curve of the frequency spectrum for the velocity. Tremor is directly related to fine motor actions such as pinching, writing, drawing and other small movements. Therefore, it is interesting to analyse the level of tremor in children as they grow up, because it will be higher or lower depending on their motor skills development.

An interesting article in this line was the work presented by Xu, Zhou, and Lyu (2014), where a variety of touch gestures were used to enhance the security and privacy of users based on the touch operations performed on their smartphone screens. Through the analysis of touch gestures such as swipe, drag and drop, tap or pinch, among others, the authors proposed a total of 132 features that identify the way each user interacts with the mobile device, achieving an Equal Error Rate (EER) of around 10% for all types of gestures and 1% for the swipe operation where the Largest Deviation Point (LDP) was considered. Another interesting study on this line was carried out by Vatavu, Anthony and Brown (2015), where through the features extracted using the touch coordinates x and y , it was possible to detect the age group of the users reaching up to 86.5% accuracy. A similar study was conducted in Zaccagnino, Capo, Guarino, Lettieri, and Malandrino (2021), where the authors proposed a novel approach to protect society from online threats through the interaction of 147 participants with six micro-games in an Android app. A dataset of more than 9000 touch gestures was created, characterizing how participants interact with the device and achieving results up to 88% accuracy detecting impostors.

3. ChildCI framework

As we preliminary presented in Tolosana, Ruiz-Garcia et al. (2022), ChildCI is an on-going project mainly intended to improve the understanding of children's motor and cognitive development along time through the interaction with mobile devices. Stylus and finger are used as acquisition tools, capturing data and storing it in our novel ChildCI database (ChildCIdb_v1²). This is a database collected in collaboration with the school GSD Las Suertes in Madrid (Spain), which is planned to be extended yearly, allowing for interesting longitudinal studies. To the best of our knowledge, ChildCIdb_v1 is the largest and most diverse publicly available Child-Computer Interaction (CCI) dataset to date on the topic of the interaction of children with mobile devices. It is composed of 438 children in the ages from 18 months to 8 years, grouped in 8 different educational levels according to the Spanish education system. In addition, during the capture process other interesting information from the children is also collected: (i) previous experience using mobile devices, (ii) grades at the school, (iii) attention-deficit/hyperactivity disorder (ADHD), (iv) birthday date, (v) prematurity (under 37 weeks gestation). All this additional metadata makes the project more powerful and interesting, allowing for multiple lines of future research. This dataset is considered in the experimental framework of this study.

In particular, 6 different tests are considered in ChildCI, grouped in 2 main blocks: (i) touch, and (ii) stylus. Each one has a maximum amount of time to be performed and requires different levels of neuro-motor and cognitive skills to be completed correctly. We briefly present next each of the tests:

• Touch Block

- **Test 1 - Tap and Reaction Time:** the screen shows 6 burrows and a single mole. When the children touch the mole using their finger it disappears from the current burrow and appears in another one at random. A total of 4 moles must be touched to finish the test. Just a single finger is needed to complete the test. This test requires fine motor skills (tap in a small area), as well as hand-eye coordination. The maximum time for this test is 30 s.
- **Test 2 - Drag and Drop:** a carrot appears on the left side of the screen and a rabbit on the right. The aim is to touch the carrot, drag it from left to right and drop it on the rabbit. Just a single finger is needed to complete the test. This test combines fine motor skills (tap in a small area), pressure control, hand-eye coordination, and tracking of movement. The maximum time for this test is 30 s.
- **Test 3 - Zoom In:** two red circles and a little rabbit appear on the screen. The children have to enlarge the rabbit and put it inside these circles for a short period of time. The rabbit can be only enlarged/shortened using two fingers. This test involves fine motor skills (put the rabbit inside two circles), coordination of the fingers (usually thumb and index finger) for the pinch movement, and accurate perception of the force. The maximum time for this test is 30 s.
- **Test 4 - Zoom Out:** the goal is similar to Test 3, except that in this case the rabbit is bigger and the children have to reduce its size to fit it inside the two red circles. Two fingers are needed to complete the test. This test requires the same motor and cognitive skills as Test 3 to be completed. The maximum time for this test is 30 s.

• Stylus Block

- **Test 5 - Spiral Test:** a black spiral appears on the screen. The children, using the pen stylus, must draw along the spiral from the inner to the outer part, always trying to keep inside the black line that forms the spiral. This test requires precise hand-eye coordination, fine motor skills to control the stylus movement and follow a line without getting off the path, and visual tracking. The maximum time for this test is 30 s.
- **Test 6 - Drawing Test:** the outline of a tree appears on the screen and the children must colour it in as well as they can. This test involves hand-eye coordination, fine motor skills to control the stylus and stay within the outline of the tree, as well as planning and organization to colour it properly and fast. The maximum time for this test is 2 min.

Examples of the different tests can be seen in Fig. 1, grouped by age. We include red and green marks along the tests to provide a better comprehension of the children interaction along the different age groups.

4. Method

In order to shed some light on the questions considered in this study, i.e., (i) validate the discriminative power of the different tests included in ChildCI, and (ii) analyse whether there is any relationship between the chronological age of the children and their motor and cognitive development, the experimental framework of this study is carried out for the task of automatic children age group detection based on their motor and cognitive behaviours. Section 4.1 describes the feature set proposed for each of the tests considered in ChildCIdb_v1. Section 4.2 summarizes the feature selection techniques considered. Finally, Section 4.3 indicates the different classification algorithms analysed.

² https://github.com/BiDAlab/ChildCIdb_v1.

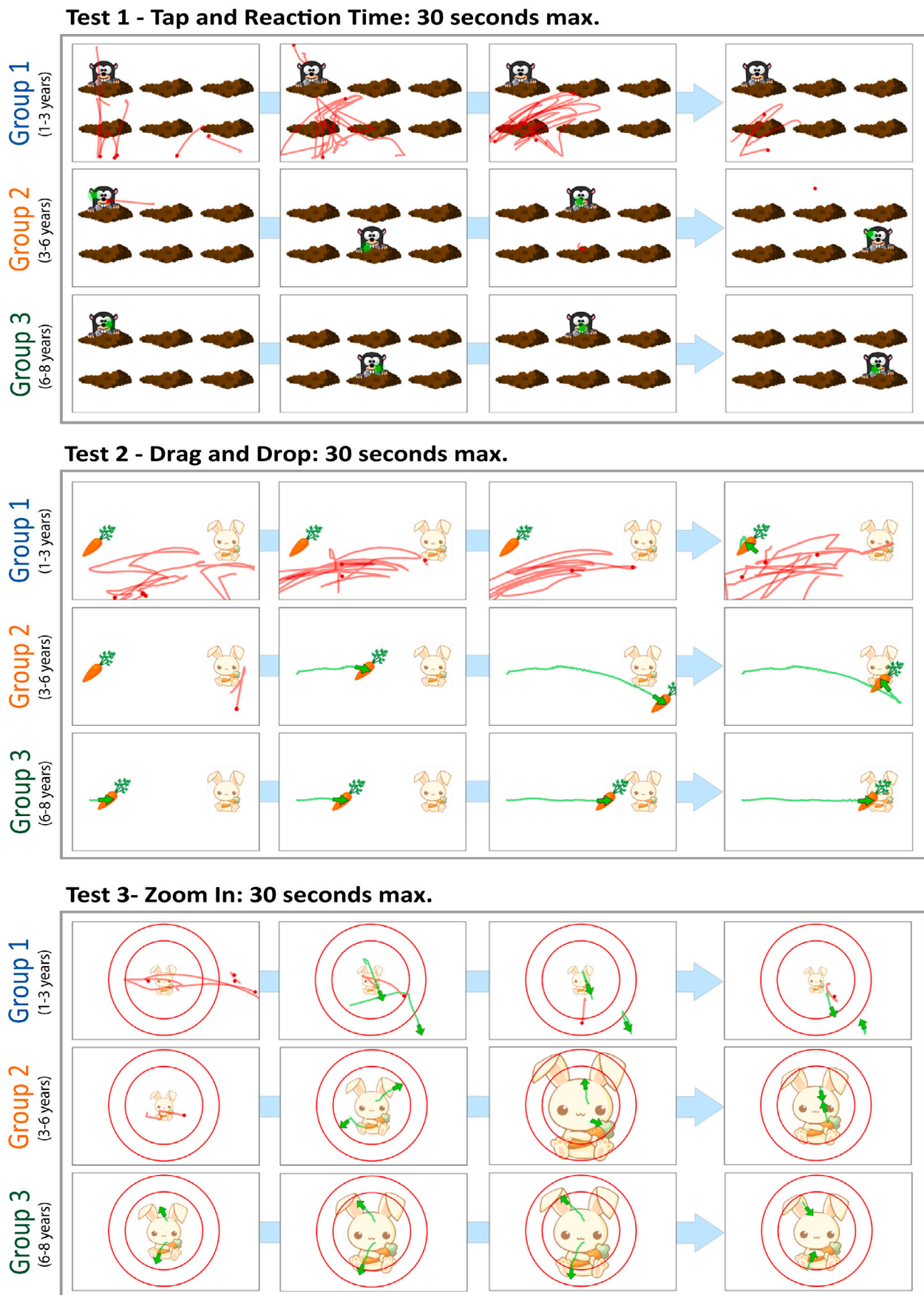


Fig. 1. Examples of the ChildCldb_v1 tests performed by three different children age groups: **Group 1** (1 to 3 years), **Group 2** (3 to 6 years), and **Group 3** (6 to 8 years). From Test 1–4, red marks indicate a poor interaction of the child compared to what expected in the test. Green marks indicate correct interaction. These marks are included here for a better comprehension. Representative full video recordings of the different educational levels are available at https://github.com/BiDALab/ChildCldb_v1.

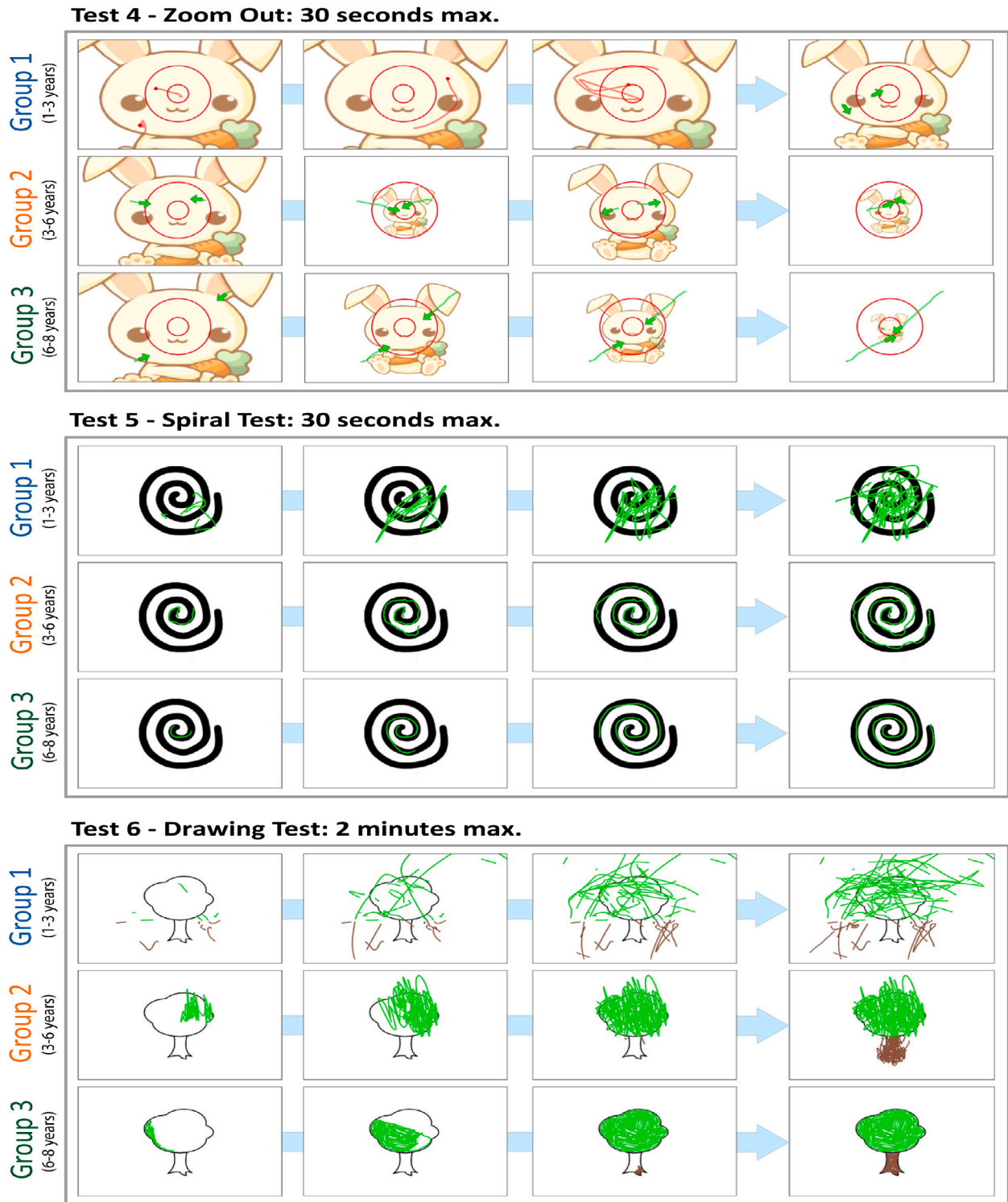


Fig. 1. (continued).

4.1. Feature extraction

During the data collection process, each child performs the set of tests shown in Fig. 1. This section presents the proposed feature sets for each test. In total, 111 global features are extracted referring to different types of skills.

- **Test 1 - Tap and Reaction Time** (Table 1): a set of 5 specific features is proposed.

- **Test 2 - Drag and Drop** (Table 2): 28 features are proposed. In particular, 2 of them are proposed in this work and 26 are inspired on the study by Xu et al. (2014).
- **Test 3 and 4 - Zoom In/Out** (Table 3): a set of 20 features is proposed, 8 of them proposed in this work, 4 based on the study conducted in Zaccagnino et al. (2021) and the remaining 8 inspired from Xu et al. (2014).
- **Test 5 - Spiral Test** (Table 4): for this test, 24 features are proposed. In particular, 3 of them are based on the study conducted

Table 1

Set of features proposed for “Test 1: Tap and Reaction Time”.

#	Feature description
1	Average Distance Between Tap and Centre of Mole
2	Standard Deviation Distance Between Tap and Centre of Mole
3	Maximum Distance Between Tap and Centre of Mole
4	Minimum Distance Between Tap and Centre of Mole
5	Number of Moles Touched

Table 2Set of features proposed for “Test 2: Drag and Drop”. The features highlighted in **bold** are specifically designed for this test. The rest are inspired from Xu et al. (2014). LDP refers to the Largest Deviation Point.

#	Feature description	#	Feature description
1	Average LDP Size	2	Standard Deviation LDP Size
3	Average LDP Velocity	4	Standard Deviation LDP Velocity
5	Average Start-to-LDP Latency (ms)	6	Standard Deviation Start-to-LDP Latency (ms)
7	Average Straight Start-to-LDP Length	8	Standard Deviation Straight Start-to-LDP Length
9	Average Start-to-LDP Direction	10	Standard Deviation Start-to-Stop Direction
11	Average Start-to-Stop Latency (ms)	12	Standard Deviation Start-to-Stop Latency (ms)
13	Average Straight Start-to-Stop Length	14	Standard Deviation Straight Start-to-Stop Length
15	Average Start-to-Stop Direction	16	Standard Deviation Start-to-Stop Direction
17	Average LDP-to-Stop Latency (ms)	18	Standard Deviation LDP-to-Stop Latency (ms)
19	Average Straight LDP-to-Stop Length	20	Standard Deviation LDP-to-Stop Length
21	Average LDP-to-Stop Direction	22	Standard Deviation LDP-to-Stop Direction
23	Average Start Point Velocity	24	Standard Deviation Start Point Velocity
25	Average Stop Point Velocity	26	Standard Deviation Stop Point Velocity
27	The Carrot is Touched in the First Pen-Down	28	Carrot Ends Up in the Rabbit (Target)

Table 3Set of features proposed for “Test 3 and 4: Zoom-in and Zoom-out”. The features highlighted in **bold** are specifically designed for this test. The rest are inspired from Xu et al. (2014) and Zaccagnino et al. (2021). Two fingers are needed for these tests. FC refers to the first finger curve, SC to the second finger curve, and V to the velocity vector.

#	Feature description	#	Feature description
1	Total Time on Target (ms)	2	Reaction Time Until Using 2 Fingers (ms)
3	Maximum Scale	4	Minimum Scale
5	Average Scale	6	Standard Deviation Scale
7	# Samples Using 2 Fingers	8	# Samples Using 1 Finger
9	Average V_x FC	10	Average V_y FC
11	Average V_x SC	12	Average V_y SC
13	FC Trajectory Length	14	SC Trajectory Length
15	FC Trajectory Velocity	16	SC Trajectory Velocity
17	Start Distance Between Both Fingers	18	Stop Distance Between Both Fingers
19	FC Straight Length	20	SC Straight Length

in Ishii et al. (2020), 14 are inspired from Solé-Casals et al. (2019), 2 are based on the results obtained by Lin et al. (2018) and the remaining 5 are proposed in this work.

- **Test 6 - Drawing Test:** we consider the 34 features originally presented in Tolosana, Ruiz-Garcia et al. (2022).

The features studied in this work cover aspects such as: (i) the reaction time to touch the screen, (ii) the amount of time touching the target, (iii) the number of fingers used, and (iv) whether the child finishes the test (4 moles are touched, the carrot ends up on the rabbit, the rabbit is properly scaled, etc.), among others.

In addition to the 111 global features presented above, 114 features based on preliminary studies in the field of HCI and related to Time, Kinematic, Direction, Geometry, and Pressure information are also considered (Martinez-Diaz, Fierrez, Galbally, & Ortega-Garcia, 2008; Tolosana, Vera-Rodriguez, Fierrez and Ortega-Garcia, 2015), forming a final set of 225 global features in total.

4.2. Feature selection

The following feature selection techniques are used to choose the most discriminative features for each test from the total set originally extracted.

- **Sequential Forward Floating Search (SFFS):** this is a widely used feature selection algorithm that searches for the best-correlated

subset of features using a specific optimization criteria. On the one hand, the solution offered by this algorithm is suboptimal because it does not take into account all possible combinations, but on the other hand, it does consider correlations between features, achieving high-accuracy results (Tolosana, Vera-Rodriguez, Ortega-Garcia and Fierrez, 2015). The implementation considered in this study has been provided by the MLxtend library.³

- **Genetic Algorithm (GA):** this is a metaheuristic algorithm based on Charles Darwin’s theory of evolution. It is presented in our previous work (Tolosana, Ruiz-Garcia et al., 2022) and is mainly inspired by the natural selection process of evolution, where over generations and through the use of operators such as mutation, crossover, and selection, a positive evolution towards better solutions occurs. It is widely used as a feature selection method as it reduces computational time, improves prediction performance, and allows for a better understanding of data (Chandrashekar & Sahin, 2014; Saibene & Gasparini, 2023). Our public version of this library developed in Python can be found on GitHub.⁴ In our experiments, we have considered the parameters that provided the best performance during the development stage: an initial population = 200, a random number of generations = 100, a crossover rate = 0.6, and a mutation rate = 0.05.

³ <http://rasbt.github.io/mlxtend/>.

⁴ <https://github.com/BiDAlab/GeneticAlgorithm>.

Table 4

Set of features proposed for “Test 5: Spiral Test”. The features highlighted in **bold** are specifically designed for this test. The rest are inspired from Ishii et al. (2020), Lin et al. (2018) and Solé-Casals et al. (2019). R_n refers to the radial coordinates, θ_n to the angular coordinates, and t_n to sample-to-sample times in seconds.

#	Feature description	#	Feature description
1	Spiral Length	2	Average (Distance Between Points)
3	STD (Distance Between Points)	4	Response Time (s)
5	Sample Entropy (SENT) [m = 3, r = 0.2]	6	Mean Absolute Value (MAV) $\frac{1}{N} \sum_{i=1}^N R_i $
7	Variance (VAR) $\frac{1}{N-1} \sum_{i=1}^N R_i - \mu ^2$	8	Root Mean Square (RMS) $\sqrt{\frac{1}{N} \sum_{i=1}^N R_i^2}$
9	Log Detector (LOG) $e^{\frac{1}{N} \sum_{i=1}^N \log(R_i)}$	10	Waveform Length (WL) $\sum_{i=1}^{N-1} R_{i+1} - R_i $
11	Standard Deviation (STD) $\sqrt{\frac{1}{N-1} \sum_{i=1}^N R_i - \mu ^2}$	12	Difference Absolute Standard Deviation (ACC) $\sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} R_{i+1} - R_i ^2}$
13	Fractal Dimension (FD) [Higuchi's Algorithm with m = 5]	14	Maximum Fractal Length (MFL) $\log(\sum_{i=1}^{N-1} R_{i+1} - R_i)$
15	Integrated EMG (IEMG) $\sum_{i=1}^N R_i $	16	Simple Square EMG (SSI) $\sum_{i=1}^N R_i^2$
17	Zero Crossing (ZC) [# Times the Signal Crosses Its Mean]	18	Slope Sign Change (SSC) [# Times the Slope of the Sign Changes]
19	Mean of Radial Difference Per Radian $\frac{1}{N} \sum_{i=1}^{N-1} \left \frac{R_{i+1} - R_i}{\theta_{i+1} - \theta_i} \right $	20	Mean of Radial Difference Per Second $\frac{1}{N} \sum_{i=1}^{N-1} \left \frac{R_{i+1} - R_i}{t_{i+1} - t_i} \right $
21	# Maximums in R_n	22	# Minimums in R_n
23	Global Maximum Quartile of R_n	24	Global Minimum Quartile of R_n

4.3. Classification algorithms

All classifiers are publicly available on Scikit-Learn.⁵ The parameters used for each classifier are those with the best performance during the development stage.

- *Support Vector Machines (SVM)*: this algorithm builds a hyperplane or set of hyperplanes in a high- or infinite-dimensional space that differentiates the classes as well as possible. In our case, the regularization parameter is 0.1, the kernel type is “polynomial” with 3 degrees and the coefficient is “scaled”.
- *Random Forest (RF)*: this is an ensemble method consisting of a defined number of small decision trees, called estimators. A combination of the estimator’s decisions is produced to get a more accurate prediction. In our experiments, the number of estimators is 10, the function to measure the quality of a split is “gini” and the maximum depth of the tree is 75.

The SVM and RF classifiers are selected in this study due to their popularity in several machine learning tasks. They offer high versatility and solid results, as can be seen in Tolosana, Ruiz-Garcia et al. (2022), outperforming other machine learning approaches.

5. Experiments and results

5.1. Experimental protocol

The experimental protocol considered in this work is designed with the aim of age group detection based on the children interaction behaviour. The following 3 different age groups are considered: **Group 1** (children aged 1 to 3 years), **Group 2** (children aged 3 to 6 years), and **Group 3** (children aged 6 to 8 years). It is important to remark that this age categorization differs from Piaget’s stages as we focus on specific motor-cognitive skills (tap, drag and drop, pinch, etc.) rather than on more generic skills presented by Piaget’s levels. This decision is also supported by previous approaches in the literature that correlates

children’s gestures with ages (Crescenzi Lanna & Grané Oro, 2019; Vatavu, Cramariuc et al., 2015), and by the neurologists, psychologist, and educators of GSD School during the acquisition of the database. ChildCidb_v1 is divided into 2 data subsets: development (80%) and evaluation (20%). The development dataset is used for the training of the age group detection systems whereas the evaluation dataset is used to test the performance of the trained systems, excluding the children considered in the development dataset. In addition, and only during the development stage, a data augmentation technique is used as the data available in Groups 1 and 3 are smaller than in Group 2. This technique is called SMOTE and is publicly available in the Imbalanced-Learn toolbox.⁶ To provide a better analysis of the results, k -fold cross-validation with $k = 5$ is used, showing the final evaluation results of the 5-fold cross-validation. All experiments are run on a machine with an Intel i7-9700 processor and 32 GB of RAM.

5.2. Experimental results

This section analyses the performance of the methods presented above to the children age group detection task based on motor and cognitive behaviours when interacting with mobile devices. The analysis is carried out in two different stages: (i) a first test-by-test analysis is performed, and (ii) then a combination of tests is conducted to analyse the potential of the ChildCI tests as a whole. The results obtained are measured in terms of Accuracy (%).

1. **Single-Test Scenario:** Table 5 shows the results obtained in each test using the different classifiers and feature selectors considered.

We first analyse the results test by test using the best results achieved for each one. As can be seen, Test 6 obtains the best accuracy (90.45%), while the worst result is for Test 3 (81.33%). Children can draw the tree in many different ways. Therefore, in Test 6 they have more freedom to interact with the device and, as a result, the variation between groups can be better observed, leading to high accuracy in the age group detection task.

⁵ <https://scikit-learn.org/stable/>.

⁶ <https://imbalanced-learn.org/stable/>.

Table 5

Results achieved in terms of Accuracy (%) over the final evaluation dataset of ChildCIdb_v1 for each of the tests considered. Standard deviations are reported in brackets. We highlight in **bold** the feature selector and classifier with the best results.

		SFFS		GA	
		SVM	RF	SVM	RF
Finger	Test 1: Tap and Reaction	89.79 ($\pm 2.19\text{e-}02$)	87.71 ($\pm 2.41\text{e-}02$)	88.51 ($\pm 2.52\text{e-}02$)	85.00 ($\pm 2.25\text{e-}02$)
	Test 2: Drag and Drop	87.23 ($\pm 2.87\text{e-}02$)	83.89 ($\pm 4.77\text{e-}02$)	85.47 ($\pm 2.29\text{e-}02$)	83.09 ($\pm 3.95\text{e-}02$)
	Test 3: Zoom In	80.22 ($\pm 2.55\text{e-}02$)	78.14 ($\pm 2.05\text{e-}02$)	81.33 ($\pm 9.94\text{e-}03$)	78.15 ($\pm 2.49\text{e-}02$)
	Test 4: Zoom Out	79.74 ($\pm 2.08\text{e-}02$)	79.26 ($\pm 5.32\text{e-}02$)	82.45 ($\pm 6.06\text{e-}02$)	80.22 ($\pm 4.05\text{e-}02$)
Stylus	Test 5: Spiral Test	88.67 ($\pm 2.34\text{e-}02$)	82.93 ($\pm 1.95\text{e-}02$)	85.16 ($\pm 1.90\text{e-}02$)	81.33 ($\pm 2.10\text{e-}02$)
	Test 6: Drawing Test	90.45 ($\pm 4.47\text{e-}02$)	88.69 ($\pm 5.09\text{e-}02$)	81.51 ($\pm 5.56\text{e-}02$)	80.37 ($\pm 5.04\text{e-}02$)

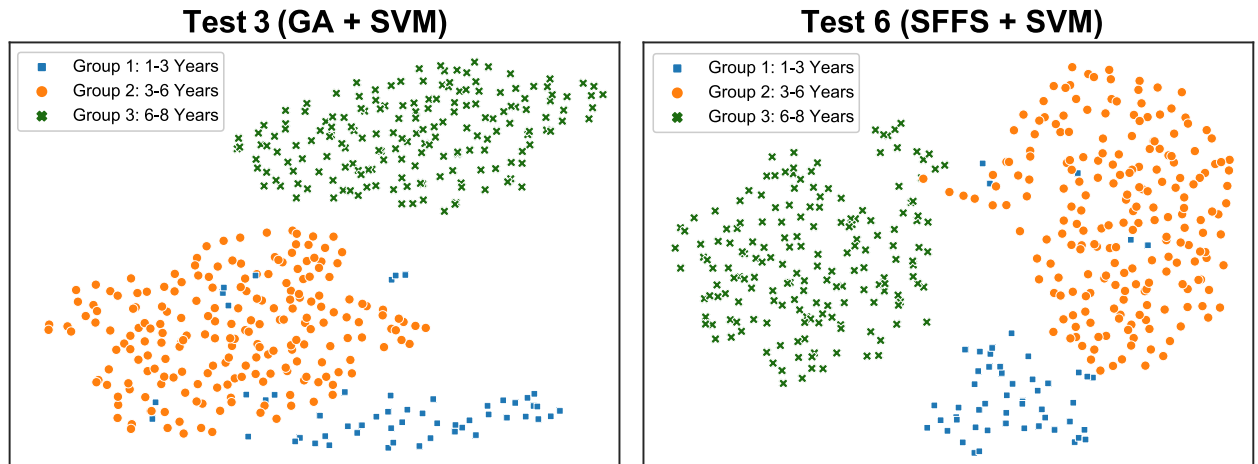


Fig. 2. Examples of children age groups formed based on the motor and cognitive features proposed in this study. Three groups can be observed in each graph: **Group 1** (1 to 3 years), **Group 2** (3 to 6 years), and **Group 3** (6 to 8 years). Each point refers to one child of ChildCIdb_v1.

Analysing the results according to the classifier studied, SVM always achieves better results than RF, regardless of the feature selector used. In particular, SVM achieves an average accuracy of over 86%, while for RF the average is less than 83%.

It is also interesting to analyse the results by the type of feature selectors considered. In most cases, SFFS provides the best results, achieving in Test 1, Test 2, Test 5 and Test 6 rates above 87% accuracy. Nevertheless, GA performs better for Tests 3 and 4, reaching 81.33% and 82.45% accuracy. This proves the potential of our proposed feature selector algorithm that is publicly available.⁷

In addition, we analyse the results according to the writing input used (stylus/finger). Always looking at the best tests for each input method, the results obtained in terms of accuracy are similar, indicating that the input method used is not really relevant for the age group detection task.

In order to show the results in a more visual way, we use a popular visualization technique, called Uniform Manifold Approximation and Projection (UMAP) (McInnes, Healy, & Melville, 2018). Fig. 2 shows 2 examples of the children age groups formed based on the motor and cognitive features proposed in this study. Therefore, those children belonging to the same age group and whose motor and cognitive interactions on each test are similar should appear in the same group and placed contiguously to each other. As can be seen in both cases, there is a point cloud with 3 distinct groups, indicating a high correlation between the age of the children and the way they interact with mobile devices. However, some children are in a different point cloud

to their own age group. For example, in the results of Test 6 in Fig. 2, we can see that there are children from **Group 1** who are in the point cloud of **Group 2**. These particular cases could be an indicator that these children have more advanced motor and cognitive aspects than their age group.

In view of the results obtained, we can shed some light on the key questions analysed in this study. First, the validation of the discriminative power of the different tests included in the ChildCI framework. The results achieved in Table 5 prove that ChildCI tests are able to measure different children motor and cognitive features for the different ages. Second, the analysis of whether there is any relationship between the chronological age of the children and their motor and cognitive development. The point clouds shown in Fig. 2 indicate that there seems to be a good relationship between the motor and cognitive features proposed in this study and the chronological age of the children. Finally, for completeness, we analyse in Fig. 3 the type of gestures and tests children are able to perform according to their chronological age. Test 6 (Drawing Test) is considered correctly completed when at least 70% of the tree surface is coloured. Looking at those gestures performed with the finger (from Test 1 to 4), we can see how gestures such as tap or drag and drop are easily achievable from the age of 2–3 years. However, more complex gestures such as zoom-in (Test 3) and zoom-out (Test 4) are strongly influenced by the age of the child, as until the age of 3–5 years old they are not able to complete them in general. Similar conclusions can be observed for those cases where the child interacts with the stylus (Test 5 and Test 6), mainly due to the fine motor skills needed to perform this type of tests.

⁷ <https://github.com/BiDAlab/GeneticAlgorithm>.

Table 6

Best average results in terms of Accuracy (%) for all the possible combinations, in groups of 2, 3, 4, 5, and 6 tests ($C_{6,2}$, $C_{6,3}$, $C_{6,4}$, $C_{6,5}$ and $C_{6,6}$), of the different ChildCldb_v1 tests. Standard deviations are reported in brackets. We highlight in **bold** the combination with the best result.

Combination	Test 1: Tap and Reaction Time	Test 2: Drag and Drop	Test 3: Zoom In	Test 4: Zoom Out	Test 5: Spiral Test	Test 6: Drawing Test	Accuracy (%)
C2				✓		✓	89.59 (± 2.64)
C3				✓	✓	✓	91.40 (± 2.47)
C4			✓	✓	✓	✓	91.68 (± 2.75)
C5	✓		✓	✓	✓	✓	92.86 (± 2.19)
C6	✓	✓	✓	✓	✓	✓	93.08 (± 2.37)

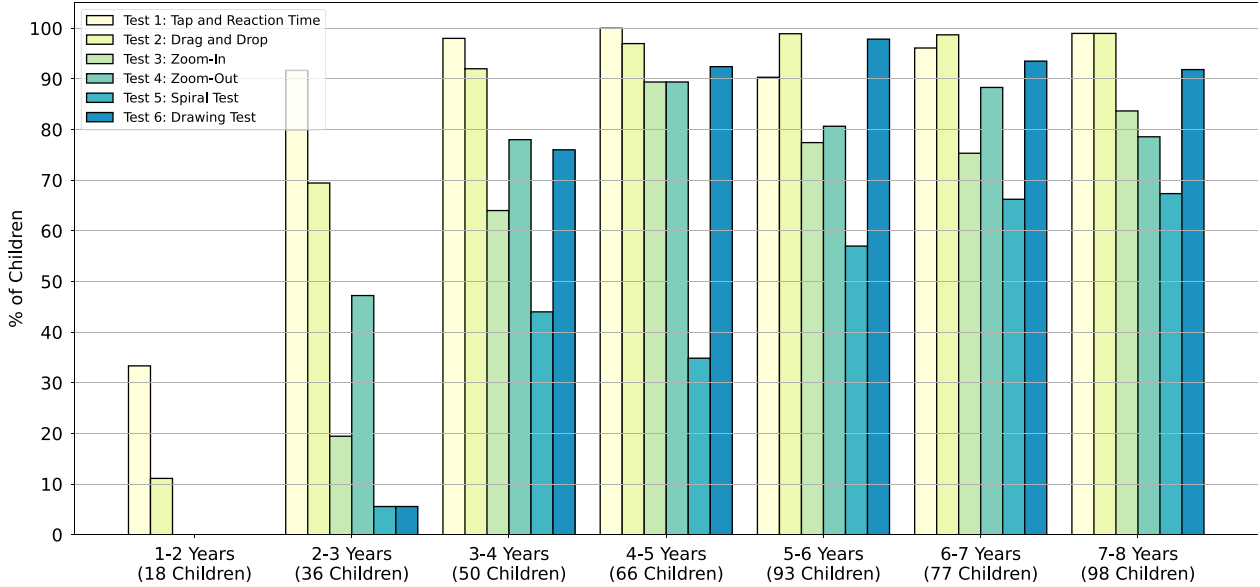


Fig. 3. Percentage of ChildCI tests completed by the 438 children data captured in ChildCldb_v1 according to their chronological ages.

2. Multiple-Test Scenario: In ChildCI framework there are 6 tests in total, with the corresponding best machine learning models for each test (previous experiment). The present experiment analyses the potential of combining these tests. We consider combinatorial operations with all possible test combinations. The number of combinations is indicated by the following equation:

$$C_{n,x} = \binom{n}{x} = \frac{n!}{x!(n-x)!} \quad (1)$$

The number of total observations is represented by n whereas x refers to the number of selected elements. We combine the individual tests into groups of 2, 3, 4, 5, and 6 tests (all tests together). In total there are 57 possible combinations: (i) 15 combinations in groups of 2 tests, (ii) 20 combinations in groups of 3 tests, (iii) 15 combinations in groups of 4 tests, (iv) 6 combinations in groups of 5 tests, and (v) 1 combination of all tests together.

In particular, the machine learning models trained for each test during the development stage generate 3 probabilities (one for each children age group, values between 0 and 1) whose sum cannot exceed 1. To combine the different tests, a majority voting ensemble is considered. Then, the associated age group of a child is determined by the highest number of votes among the classifiers. For tie-breakers, an average of the probabilities generated for each set of grouped tests is calculated, with the highest value determining the age group associated with the child.

In order to generate reliable results, 25 random k -fold cross-validation are performed ($k = 5$). Table 6 shows the best average results in terms of accuracy for each group of test combinations

(from 2-test to 6-test). As we can observe, the more tests are considered, the better the results are. In particular, the combination of all tests (C6) offers the best result, reaching 93% accuracy. Therefore, this result proves that (i) all tests considered in ChildCI frameworks are valuable, and (ii) a combination of tests is a good practice to obtain better results for the children age group detection task.

Finally, for completeness, we include a statistical analysis through the Kruskal–Wallis test among the 5 combinations presented in Table 6 to check whether the results are statistically significant. We propose the following hypothesis:

- H_0 (Null Hypothesis): There are no significant differences between the test combinations.
- H_1 (Alternative Hypothesis): There are significant differences between the test combinations.

The Kruskal–Wallis test shows a p-value of $6.24e-06$. Therefore, setting a significance value $\alpha = 0.05$ and a Bonferroni-corrected significance value ($\alpha_{cor} = 0.05/5 = 0.01$), H_0 can be rejected ($p\text{-value} < \alpha_{cor}$), and a significant difference between the mean accuracies of the combinations is demonstrated. Based on these results, we applied a post hoc Mann–Whitney U test to find out between which pairs of combinations there are significant differences in the results. Table 7 shows the results of the Mann–Whitney U test and if the null hypothesis H_0 is rejected. As can be seen, in all pairwise comparisons related to the C6 combination (combination of all tests) there are significant differences in the results obtained, with the exception of the comparison with C5, where it appears that including Test 2 (Drag and Drop) is not significant for an α_{cor} value of 0.01.

Table 7

Pairwise comparison results with Mann–Whitney U test and Bonferroni correction for the combinations of tests.

Pairwise comparison	p-value (Mann–Whitney U test)	H_0 is rejected ($<\alpha_{cor} = 0.01$)
C2 vs. C3	0.17	No
C2 vs. C4	0.42	No
C2 vs. C5	1.71e−04	Yes
C2 vs. C6	6.97e−05	Yes
C3 vs. C4	0.58	No
C3 vs. C5	6.27e−04	Yes
C3 vs. C6	1.89e−03	Yes
C4 vs. C5	1.32e−03	Yes
C4 vs. C6	5.19e−04	Yes
C5 vs. C6	0.51	No

6. Conclusion and future work

The proposal of automatic methods that quantify the motor and cognitive development of the children through the interaction with mobile devices is one of the main motivations of our ChildCI framework. As a first step to reach that future goal, this study proposes a comprehensive analysis evaluating the discriminative power of the tests presented in our ChildCI framework, and an analysis of whether there is any relationship between the chronological age of the children and their motor and cognitive development.

For each of the tests considered, a robust set of features representing cognitive and motor aspects of children during interaction with mobile devices is presented. The experimental framework of this study is carried out for the automatic children age group detection task based on similar motor and cognitive behaviours.

The results achieved shed some light on the questions and contributions analysed in this study. Indeed, there is a relationship between children's chronological age, their motor and cognitive development and the type of test they are able to perform when interacting with mobile devices. Fig. 2 shows a high correlation between the age of the children and the way they interact with the devices, denoting the way in which the children perform the tests can give a rough indication of their chronological age group. Nevertheless, 100% accuracy is not achieved in the age group detection task because children's evolution is a maturation process. This means that children of the same age group may have more/less advanced motor and cognitive aspects depending on their development, as can be seen in Fig. 3.

In addition, the potential and discriminative power of the tests included in the ChildCI framework is proved. The results achieved in Tables 5 and 6 demonstrate that ChildCI tests are able to measure different children motor and cognitive features for the different ages. This indicates both the correct design of the tests, discussed and approved by specialists such as neurologists, child psychologists and educators, and their inherent applicability to other research problems around e-Learning and e-Health. In particular, such kind of applications could include: (i) serving as a precise and personalized assessment tool to detect delays or difficulties in children's motor and cognitive development, enabling early interventions (Acien et al., 2022; Gomez, Morales, Fierrez, & Orozco-Arroyave, 2023); (ii) providing a platform for the development of personalized e-learning applications (Daza et al., 2022), by adapting the content and challenges to individual needs of children, among others.

Future works will be oriented towards: (i) relating children's interaction information with mobile devices to the other metadata stored in ChildCIdb (school grades, ADHD, previous experience using mobile devices, prematurity, etc.), (ii) presentation of new versions of the database analysing longitudinally the evolution of children when performing the different ChildCIdb tests, and (iii) take advantage of ChildCIdb's potential in other e-Health and e-Learning research areas and problems.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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