Smartphone Haptics can Uncover Differences in Touch Interactions Between ASD and Neurotypicals

IVONNE MONARCA, FRANCELI L. CIBRIAN, ISABEL LÓPEZ HURTADO, and MONICA TENTORI

Utilizing touch interactions from smartphones for gathering data and identifying digital markers for screening and monitoring neurological disorders, such as Autism Spectrum Disorder (ASD), is an emerging area of research. Smartphones provide multiple benefits for this kind of study, including unobtrusive data collection via built-in sensors, integrated haptic feedback systems, and the capability to create specialized applications. Acknowledging the significant yet understudied presence of tactile processing differences in individuals with ASD, we designed and developed *Feel and Touch*, a mobile game that leverages the haptic capabilities of smartphones. This game provides vibrotactile feedback in response to touch interactions and collects data on these interactions. We conducted a deployment study with 83 Mexican children who played Feel and Touch to capture their interactions with the game. Our analysis, comparing touch interactions between children with ASD and neurotypical (NT) peers, uncovered three digital markers based on phone tilt and touch patterns that distinguish the two groups. Additionally, we demonstrated the ability of a machine learning model to accurately classify these interactions between ASD and NT children. Our findings discuss the implications in terms of accessibility and ubiquity, as well as the possibilities for the development of digital markers and their application in pervasive computing for healthcare.

CCS Concepts: • **Human-centered computing → Haptic devices**; *Smartphones*; • **Applied computing → Life and medical sciences**.

Additional Key Words and Phrases: Vibrotactile Pattern, Digital Markers, Autism Spectrum Disorder

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1 INTRODUCTION

Autism spectrum disorder (ASD) is a complex neurodevelopmental disorder that is marked by a wide array of social and behavioral symptoms [6]. There is consensus in the field that early diagnosis of ASD can not only impact early access to high impact treatments but also support the development of an ASD-friendly environment [37] improving outcomes for ASD children. Obtaining a full diagnosis usually requires working with specialists who use validated tests, such as the Denver Scale, the Autism Diagnostic Observation Schedule, Second Edition (ADOS-2), and the Autism Diagnostic Interview Revised (ADI-R). However, conducting these tests can be prohibitively expensive, especially in contexts like Mexico. The cost of a comprehensive diagnostic assessment is approximately $10,000 Mexican Pesos, equivalent to around 2.3 months of work for individuals earning the minimum wage. Consequently, the screening and diagnosis of ASD in Mexico are often beyond the reach of the majority of the population, making them costly, delayed, and prone to errors [15].

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In recent years, there has been a focus on identifying digital markers to support the early detection and screening of ASD [25].Despite not being entirely objective, digital markers offer a valuable approach to ubiquitously collecting quantifiable behavioral data using different technologies, like smartphones. This data can be highly relevant to the screening, diagnosis, and monitoring of healthcare delivery in ASD [66]. The extraction and selection of digital markers for children with ASD opens up new possibilities for understanding neurobiological mechanisms of the disorder, as well as the development of accessible screening programs.

While few studies identifying digital markers for ASD have traditionally focused on uncovering actions related to emotional recognition and social attention [79], language [95], visual attention [72], and motor abilities [27], few have explored touch interactions in depth. Tactile processing differences are highly prevalent in over 85% of ASD children [90]. Children with ASD often either dislike being touched or carried, and they may present an excessive fascination or avoidance of certain textures or fabrics [90]. Despite this, there is very little discussion and evidence in the field investigating if the tactile processing differences exhibited by children with ASD can become a potential marker of ASD [85] and how haptic capabilities of smartphones can be best utilized to uncover such differences.

By leveraging advancements in haptic technology to stimulate the skin using actuators that replicate the tactile or kinetic properties of an object [56, 58, 86], there is an opportunity to collect data about children's touch interaction behavior in a non-invasive and accessible manner, particularly in the context of smartphones. These devices incorporate haptic sensors, such as vibration feedback and force monitoring, to deliver tactile information crucial for understanding how children engage with technology. In addition, given the significant increase in smartphone usage over the past decade, with 82.8% of people in urban areas and 62.6% in rural areas having access to a mobile phone in Mexico [50], there is a substantial opportunity to develop mobile tools that can complement existing ASD screening methods. By leveraging the widespread availability of mobile phones, such tools have the potential to offer more accessible and cost-effective screening options, tailored to the Mexican context, thereby improving the early identification and support of children with ASD.

The link between neurodevelopmental disorders and tactile processing has historically received insufficient research attention [64, 78, 91]. In this study, we extend the current state of the art by taking advantage of the affordances of haptic computing to provide tactile stimulation while children interact with a mobile phone through a haptic game named *Feel and Touch.* which incorporates vibrotactile patterns, a function of intensity, rhythm, and sharpness, representing the shape of a vibratory waveform. This paper aims to address three key research questions: 1) Can haptic mobile games be effectively used to collect touch interactions from children? 2) Which touch interaction features are most effective for classifying children with ASD using machine learning models. 3) Can alterations in tactile processing in children with ASD be measured through their interactions with haptic interfaces? . These inquiries contribute to the field of IMWUT by: 1) providing empirical evidence that demonstrates how a mobile haptic game can be used for neurotypical (NT) and children with ASD outside a clinical setting to gather their touch data, 2) sharing lessons learned from the design and development of haptic interface, which could potentially support the screening of ASD in everyday contexts, and 3) offering empirical evidence showing that tactile differences can be used to unveil digital markers that can feed a machine learning model to assist with the potentially automatic tactile screening of ASD. Our results uncovered differences between children with ASD and NT related to tilt and touch features that describe how children hold and move the mobile phone and perform touch interactions.

2 RELATED WORK

2.1 Using mobile technology to uncover digital markers

Digital markers provide quantifiable measurements of physiological and behavioral data [62]. These markers are primarily collected via wearable sensors, interactive surfaces, mobile sensors, and tracking sensors. Some digital markers replicate existing biological markers. For example, we can monitor glucose using a sensor placed on the body and transmit the information to an application [24]; on the other hand, there are digital markers that are more novel and are evolving [30].

Smartphones are increasingly utilized to gather digital markers due to their widespread use and capabilities for pervasive sensing [62]. Research indicates that smartphones can capture a broad spectrum of psychologically and physiologically relevant behaviors. For instance, their ability to uncover markers of stress-related behaviors [1], personality traits [28] and depression [41] through the analysis of phone usage, voice, and video recordings.

Additionally, a segment of research focuses on exploiting smartphone sensors to monitor health-related behaviors. Tseng et al. [97], for example, utilized the phone's accelerometer to gauge physical activity, which, in combination with other features, predicted individuals' inhibitory control. In another study, researchers trained a machine learning model using data from phone sensors—such as acceleration, gyroscope, and slope—to classify individuals into categories of cognitive performance [46]. While the potential of utilizing internal smartphone sensors to uncover digital markers is promising, this approach is largely unexplored in the field of digital markers for ASD.

2.2 Digital markers for ASD

Significant research has been conducted on identifying digital markers for children with ASD. These studies have primarily utilized sensors placed in the environment such as infrared camera [27] or Kinect Camera [3, 10] to capture movement features; eye-takings to capture gaze features [12, 72, 104]; and microphones [19, 21, 57, 94] to capture speech features.

For example, Oliveira et al. [72] employed an eye tracker to gather gaze data from 76 children with ASD and 30 NT children, aged 3 to 18 years, while they watched brief 6-second videos. Each video was divided into two parts: one showing individuals performing natural movements (e.g., a child waving a hand) and another showing geometric movements (e.g., the design of a moving fractal figure). They used the eye tracking data to extract features related to visual attention. These features were then employed to train a machine learning model for classifying children with ASD and NT, achieving an accuracy and recall of 90% and 69%, respectively. This study demonstrated that children with ASD tend to focus their gaze in the center of the image, even when there is nothing in the center, and exemplified the use of eye tracking data to extract digital markers for children with ASD.

Other studies leverage voice recordings to analyze potential patterns in the vocalizations of children with ASD, one example is the work of Lyakso et al. [57] who found significant differences in pitch values, pitch range, frequency, and voice energy between children with ASD and NT. During the study, ASD and NT children, aged 5-16, were recorded as they answered a series of questions and engaged in storytelling based on an image presented to them. Similarly, this study extracted voice-related features, and trained a machine learning model, achieving an accuracy of 60% and a recall of 67% in classifying children with ASD and NT.

Finally, another common approach to gathering digital marker is through cameras placed in the environment to study the movements and motor coordination deficits of children with ASD. A study by Ardalan et al. [10] found that children with ASD exhibit greater variability in their kinematic movements compared to NT children, with the head, shoulders, feet, and left elbow movements being the most useful in distinguishing children with ASD. Using motion capture technology, the study collected movement data from 39 children with ASD and 23 NT children aged 7 to 17 years. The children performed 10 static postures inspired by Yoga and Tai Chi practices.

These studies demonstrated the feasibility of using environmental devices to collect gaze, vocalization, and movement-related data to identify digital markers of ASD. They also highlight the importance of selecting specific features for building machine learning models capable of differentiating between children with ASD and NT children. These studies marked an important advancement in the field of digital markers for children with ASD, nonetheless the devices — such as eye tracking technology, sound equipment and motion sensing device — used to collect these digital markers are not widely available or accessible in countries with limited resources, for example, the cost of purchasing an eye-tracking system, which, is between 3,000 and 50,000 US [7]. Building on this research, another set of studies focuses on the use of interactive surfaces as an alternative approach, enabling the collection of additional markers such as touch interactions. Recent research has revealed that touch interactions with tablets can generate valuable information that could contribute to the identification of digital markers of ASD, as presented in the following section.

2.2.1 Digital markers using mobile devices. A wide range of studies have focused on collecting digital markers using tablets [9, 77] and smartphones [36]. One of the earliest significant studies leveraging mobile devices to identify digital markers of children with ASD was conducted by Anzulewicz et al. [9], who proposed the use of commercial video games on iPads to identify the motor signature of children with ASD. The study involved 37 children with ASD and 45 NT children who played two commercial video games on an iPad, each for a period of 5 minutes. During these gaming sessions, data from the screen and internal tablet sensors were recorded. A total of 262 features related to kinematic values (e.g., speed, acceleration) and touch-based metrics (e.g., number of touches) were calculated. The results obtained in this study were exceptional, the model trained with the features extracted reached an accuracy of 93% in classifying children with ASD from NT children. Additionally, significant differences were revealed in the touch behavior of children with ASD. It was found that children with ASD exerted more force in their touch interactions, performed touch interactions more rapidly, and used a larger screen area to carry out these interactions. This study marks a significant advancement in the field by offering valuable insights into how touch interactions can function as digital markers for ASD. It underscores the variations in tactile behavior among children with ASD, and lays the groundwork for future studies that seek to identify digital markers through tactile interactions.

Another example is the SensetoKnow app which uses a tablet to display short movies that prompt social attention, facial expressions, head movements, motor behaviors and name recognition. The app collects data using the tablet's front camera and quantifies it using computer vision analysis (CVA). In their 2023 study, Perochon et al. [77]. utilized the SensetoKnow app to extract 23 behavioral features from children interacting with the application. They then employed a machine learning classification model to analyze these features, and found that facing forwards, gaze, facial dynamics complexity, head movements, response to name and touch interactions were the most relevant features in the classification of ASD. Touch interactions included average touch length, average applied force, accuracy and popping rate all extracted during a pop the bubble activity.

In conjunction, this literature provides examples of employing mobile devices to collect digital markers of children with ASD, indicating that the way children with ASD interact with devices differs significantly from NT children, suggesting potential differences in motor skills or tactile processing. They also open up the possibility of using touch interaction as digital markers of ASD. However, to our knowledge, there has been limited exploration into how the haptic capabilities of mobile devices can be leveraged to stimulate touch interactions and identify digital markers of ASD. This represents a significant gap in the literature, as the use of haptics—specifically vibrotactile stimulation—in the context of ASD research is relatively novel. Children with ASD frequently experience challenges with tactile processing [64, 78, 91], which can affect their ability to respond to and interact with sensory stimuli.

2.3 Haptic technology and ASD

Haptic interfaces provide unique tactile responses to user interaction, these interfaces have garnered considerable attention in therapeutic contexts to support children in motor exercises [54, 106], sensory integration therapies [42, 55], therapeutic approaches related to emotions [83] within the context of ASD, rehabilitation [40] social skills [23] and as an educational tool to improve the reading experiences [105] and teach writing skills [74]

For example, FeelSleeve [105] is a protective glove-shaped sleeve that is placed over a tablet, and has two actuators that generate vibrotactile patterns. These patterns are associated with specific events in a story, allowing children to feel what they are reading. A study involving 44 NT children aged 6 to 9 showed that combining the narrative events with the vibrotactile patterns in FeelSleeve can effectively enhance children's reading experience.

Another example is CARBO [55], a haptic robot designed to promote tactile interactions through a set of interactive games. Results from a study conducted using CARBO revealed that children diagnosed with attention-deficit/hyperactivity disorder (ADHD) and ASD were able to interact with CARBO and found it both interesting and intuitive. This study also highlighted that the interaction patterns of children with ASD differ from those of children with ADHD, underscoring the potential of haptic feedback to identify differences in the ways children with neurodevelopmental disorders interact.

From a clinical perspective, research on haptics has focused on identifying differences in sensory processing and the development of fine motor skills in children with ASD and NT, exploring the use of devices that transmit vibrations to the fingers [38, 54, 61, 81]. For instance, a recent study conducted by Espenhahn et al.[38] with 33 children with ASD and 45 NT children aged 3 to 6 years. Participants completed vibrotactile activities involving receiving vibrations of different intensities on their fingers and answering questions about their perception. The results indicated that children with ASD had slower response times but showed greater ability to discriminate between levels of vibration intensity compared to NT children.

In summary, these studies collectively demonstrate that haptic interfaces are both well-received and effectively utilized by children diagnosed with ASD as well as NT children. Haptics also show great promise in differentiating tactile responses from children with and without ASD. Showcasing versatility, these interfaces hold promise as tools for skill assessment. However, current research indicates that the potential of haptic interfaces to identify digital markers of ASD remains underexplored.

Additionally, these insights were garnered using specialized tools designed to deliver vibrations directly to the fingers, but the accessibility of such tools has been a significant barrier. In contrast, today's mobile devices, which are widely accessible, are capable of reproducing vibrotactile patterns using haptic interfaces. By investigating how haptic feedback can be used to enhance touch interactions, our research aims to address these sensory processing difficulties and provide new insights into the development of digital markers for ASD. This approach not only contributes to the understanding of sensory processing in ASD, but also opens new avenues for creating more effective screening tools and intervention strategies tailored to the unique needs of individuals with ASD in a Latin America.

3 DESIGN AND DEVELOPMENT OF FEEL AND TOUCH

The design of *Feel and Touch* is built around the user-centered design philosophy [71], involving a comprehensive iterative process to develop a mobile haptic game augmented with vibrotactile patterns to assess tactile processing in children. To design the game, the research team conducted literature reviews, brainstorming sessions with experts and children, and multiple design and testing phases to refine the game's features and ensure the game design was appropriate for preschool-aged children.

The design process began with a comprehensive literature review to compile existing active haptic interfaces, vibrotactile patterns, and interaction gestures. Following this, we conducted 6 participatory sessions with human-computer interaction (HCI) experts, NT children, preschool teachers, and special education teachers. These sessions aimed to identify appropriate gestures associated with vibrations. During each session, we first explained the study's context and the session's objective to the participants. Then, we engaged in brainstorming to discuss key design ideas. Finally, we proposed low-fidelity prototypes and discussed their advantages and disadvantages. We analyzed the data collected during the design sessions and materialized it into sketches and storyboard scripts.

These two steps led to clear design decisions that determined the criteria for gestures captured and the vibrotactile patterns represented by the game.

Gestures. According to our experts and in line with literature [32], we select the tap and drag gesture for the game as children from 3 to 5 years old could perform easily, tap and drag.

Vibrotactile patters. The two selected gestures were linked to distinct vibrotactile patterns: the tap gesture with a flat vibration pattern and the drag gesture with a ramp vibration pattern (see Figure 1). The flat vibration pattern included three rhythm variations: slow (1-second intervals), medium (500-millisecond intervals), and fast (250-millisecond intervals), based on the repeated monotone patterns of variable-length notes studied in the literature for haptic design [45, 92, 96].For the ramp pattern, we designed variations, including ascending, descending, and mixed.

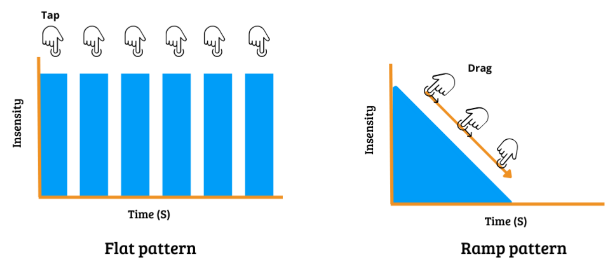


Fig. 1. Vibrotactile patterns. Left shows the Flat pattern.When children tap they will feel an array of pulse vibrations with a predefined offset that change intensity from slow (1 second between each vibration), to medium (500 milliseconds between each vibration) to fast (250 milliseconds between each vibration). Right shows ramp pattern. When children drag, the vibration intensity will increase or decrease depending on angular direction. Ascending ramps range from 40 to 100% intensity, while the descending ramps range from 100 to 40% intensity

Activities The design process also led to the design of the story and game activities. The goal of *Feel and Touch* is to help a hungry spider rebuild its web destroyed in a storm, mimicking the storytelling of the itsy bitsy spider nursery rhyme. To engage children while performing tap and drag touch interactions, *Feel and Touch* has two goal-oriented activities, *Build the web* and *Feed the spider*, and one open-ended activity, *Dancing on the web*. Following a scaffolding approach, activities are presented progressively, increasing the complexity of both the touch interaction and the type of vibrotactile pattern and its rhythm. For example, as tapping is generally easier than dragging [32], *Feel and Touch* initially presents the *Build the web* activity which requires children to tap around the screen, and then drag for a second activity.

Build the web (Figure 2-1). During this activity, children synchronize their taps anywhere on the screen with the rhythm of the flat vibration pattern. Each time they tap, the spider jumps from its current position to the location of the children's tap. This action creates a trajectory drawing, forming a colorful line that connects the spider's movement trajectory from its initial to its final location. This activity has three vibration rhythms, each with a different speed: slow (1 second between each vibration), medium (500 milliseconds between each vibration), and fast (250 milliseconds between each vibration).

Feed the spider (Figure 2-A). During this activity, children must drag the spider's feet to eat the bugs trapped in the web. A spider will catch a bug when the child releases its leg. While dragging, children will feel a ramp vibration pattern, which could be ascending, descending, or mixed of both. Ascending and descending ramps were designed to stimulate children in different ways and to assess any variance in their interactions. Vibration ramps are activated when a bug falls into the spider's web.

Dancing on the web (Figure 2-E). This activity encourages children to freely tap or drag, experiencing the corresponding vibrotactile pattern, flat, or ramps. The spider jumps when children tap and dances when being dragged.

Fig. 2. The figure presents five screenshots showing the main features of Feel and Touch. A) Build the web: this activity presents a spider in the center of the screen and colorful lines representing the web being built. B) Rewards: this screenshot represents three treasure chests vertically aligned, allowing children to choose one to collect a surprise reward that is inside. C) Feed the spider: this activity presents the spider in the center with a red line and a representation of the dragging motion required to move the spider's feet to get one of the bugs located at the end of the red line. D) Spiders collected: this shows the spiders collected through the game as a reward, so children can select their favorite to play the last activity. E) Dancing on the web: it shows the selected spider in the center of the screen, and children can tap or drag the spider; the game reproduces the vibrotactile pattern associated with each gesture. The final image shows a blue line representing a drag, the orange box representing the bounding box, and a yellow line representing the angle of the bounding box.

Tutorial. Feel and Touch incorporates a tutorial at the beginning of the game and a reward upon completing each activity consisting of unlocking a new spider (Figure 2-B). Both the tutorial and the reward act as relaxation activities that were strategically placed between the vibrotactile stimulation (i.e., the three activities) to ensure that children remain engaged without feeling overwhelmed by the vibrations [47]. If the children need guidance during the activities, the game uses both verbal and visual prompts. Verbal prompts include voice-recorded instructions in Spanish, like "Tap the screen when you feel the vibration," while visual prompts show colored dots displayed on the screen. Each prompt changes every 5 seconds in the absence of interactions from the children.

Implementation We implemented *Feel and Touch* to run on iPhone 8 and later versions with the iOS 14 operating system onwards. The iPhone 8 provides sufficient technical capabilities for our study's requirements, including processing power, touch interactions sensors, and compatibility with necessary applications. By opting for the iPhone 8, we aim to demonstrate that our game can be effectively used on more affordable versions of the iPhone, making our tool more accessible to a broader segment of the population. Feel and Touch utilized the Swift programming language, the SpriteKit game framework, and Xcode version 13.3.1 (Figure 3). To implement vibrotactile patterns, we used the haptic engine of iOS, which allows the composition and reproduction of vibrotactile patterns to provide feedback to the user.

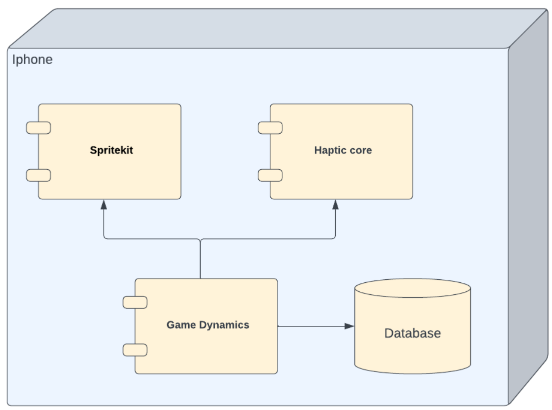


Fig. 3. The figure displays a deployment diagram showcasing the components of Feel and Touch.

Initial evaluation. The initial evaluation of *Feel and Touch* was with 5 NT children aged 3-5 and demonstrated that the game's design was effective in engaging children while testing their tactile responses. In general. children were able to 1) perform the required tab and drag gestures and respond appropriately, 2) understand and engage with the task, and 3) were not confused or frightened by the vibrations. More around the design and evaluation of the game can be seen in [65].

4 METHODS

4.1 Participants

Recruitment and data collection for this study took place in an urban city located in central Mexico. Children aged three years and older with ASD were recruited from a specialized center that focuses on children with ASD. We also recruited non-ASD or NT children from a preschool located in the same area (Table 1). Parental written consent from parents/guardians was obtained for each participant in the study, following ethical guidelines for research on minors. The study was approved by the Bioethics Committee of CICESE (no: BIOÉTICA.HUM.2021.02) and was conducted in accordance with the amended Declaration of Helsinki.

Children in the ASD group were eligible to participate in the study if they met the following criteria: 1) diagnosed with ASD level 2 of severity [1] using the Autism Diagnostic Observation Schedule, Second Edition (ADOS-2, [26]), 2) not currently taking pharmacological treatment, 3) capable of interacting with a mobile phone

[1]While there may be a greater understanding of ASD in certain contexts and the severity levels might not fully capture the complexity of the condition, these levels are still the standard within the context of our study. To align with established definitions, we will use the term 'level' to specify the severity of ASD.

and 4) between the ages of 3 to 6 years, The staff at the child care center for children with ASD was responsible for selecting children who met the inclusion criteria. To protect the privacy of participants and adhering to our ethical protocol, we did not request access to their clinical records.Children in the NT group were eligible to participate if they met the following criteria: 1) capable of interacting with a mobile phone 2) between the ages of 3 to 6 years 3) to be free from developmental disorders

We used three screening tools to get the best understanding of participants' development, and to identify children at risk of developmental delays. Furthermore, we implemented a robust screening process using three complementary assessments. Firstly, parents from both groups were asked to complete the Autism Spectrum Quotient (AQ-10), a well-established screening tool for identifying ASD test [4] and the Short Sensory Profile (SSP) survey [60] which evaluates sensory processing abilities in children, to detect any atypical sensory processing. As teachers/psychologist have most experience assessing motor skills, they completed the Ages & Stages Questionnaires-3 (ASQ-3) [2]. Any child whose test results suggested a risk for undiagnosed developmental disorders were invited to play and complete the game, but their data were excluded from the NT group. This approach allowed us to confidently categorize the remaining participants as NT, thereby enhancing the reliability of our study results.

Table 1. Characteristics of study participants reported separately for children with ASD and NT

	ASD (n = 19)	**NT (n = 36)**
Gender		
Female	5	19
Male	14	17
Age		
Mean ± SD	4.36±0.68	4.78±0.91
AQ-10 score		
Mean ± SD	6.75 ±0.95	3.18 ±0.98
SSP		
Mean ± SD	30.85 ± 6.59	20.81 ±7.63
ASQ-3		
Mean ± SD	29.16 ± 2.83	43.45 ± 11.46

4.2 Study procedure

The study lasted three months and was conducted in two locations: a typical private kindergarten and a center specializing in children with ASD. Due to the distinct samples, we couldn't bring the children to the same lab setting, so we didn't randomize the order of participants between the two groups.

We used a similar setup in both settings (Figure 2). As the game follows a scaffolding approach, we did not randomly assign the children to different setups. Participants completed two phases of the study individually, the first was completed in two sessions within the same week, and the second was completed the following week in one session. Both phases are described in detail below.

(1) Sensitization session. We conducted two sensitization sessions, each on a different day in the same week and with a five-minute duration [29, 63]. These sessions aimed to help children with ASD become more receptive to using a smartphone before playing with *Feel and Touch*, especially if they had previously associated smartphones with specific activities. During the sensitization session, children played casual games designed for children aged between 3 and 6 years.

(2) Completing the game. To minimize distractions, the study was conducted in an individual room in each setting, where all the visual and auditory stimuli were removed. The room only had a table and a child-sized chair. On top of the table, we placed an iPhone 8 with a 4.7" screen to run the game. We attached a grip phone ring holder to the back of the mobile phone to facilitate its manipulation 4. Two cameras were used in the study to enhance data collection: one to record the children's interactions and gather detailed information about their behavior, and a second camera to take photographs and document the study process. We asked the children to rest their arms on the table, allowing them to have better control of the mobile phone.Each child was accompanied during the session by a member of the research team. The head of the preschool and caregivers assisted children in navigating between their classroom and the therapy room where our intervention was held. We asked the head of the preschool and caregivers to stay at least 1.5 meters away from the children and not to touch the screen nor provide any further instructions to the child. This approach ensured that the children's interaction in the game remained uninfluenced

Children played and complete the *Feel and Touch* game. The game has a predetermined duration of 12 minutes. All children used their dominant hand to perform the touch interactions. First, they viewed the story of the spider and then completed a tutorial to ensure they understood the dynamics of the *Build the Web* activity. After engaging in the tutorial, participants completed three levels of the activity. Children then went through a similar procedure, completing a tutorial for the *Feed the spider* activity and finalized its three levels. The final part of the game is the *Dancing on the web* activity. At the end of the game, children completed a survey about their experience.

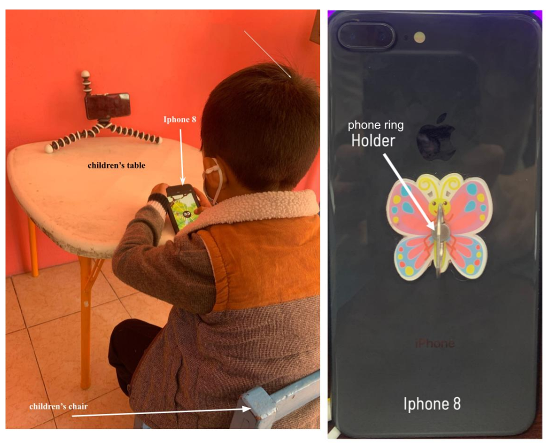


Fig. 4. The left side shows the setup used in the study, and the right side shows the phone ring holder attached to the iPhone.

4.3 Data Collection

Touch interactions were captured at a resolution of 60 frames per second during the participant's interaction with the game. The final participant interaction data were stored in a CSV file used for statistical analysis. We collected a touch interaction when a finger touches the screen and continues until the user lifts the same finger from the screen. During this time, users can either keep their finger in place (tap gesture) or move it across the screen (drag gesture) (see Figure 5). For each touch interaction we created a vector of touch-objects [49] at a time t where each vector contains the timestamp indicating when the touch occurred, size of the area in points covered by the finger in a time t, centroid of the area covered by the finger location at the time t (*x, y, z*), force of the touch occurring at the screen in N, the values of the inertial sensor at time t (accelerometer, *ax, ay, az*, and gyroscope, *gx, gy, gz*).

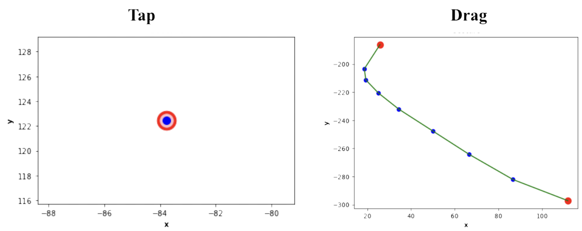


Fig. 5. The figure shows a representation of the touch interactions. The left-side shows a tap and the right-side shows a drag

In addition to the touch interactions, we recorded in the same file the time when the game gave an instruction, and we recorded the type of instruction (verbal, visual, verbal+visual).

4.4 Data Preparation

To ensure data quality, we cleaned the dataset, which involved separating the touch interactions from the instructions and removing columns with the same or no variance.

Table 2. Dataset used for the statistical analysis and machine learning process. Labeling NT for neurotypical children, ASD for children with Autism Spectrum Disorder

	NT	**ASD**
subjects (n)	36	19
Total touch interactions,	10541	6043
Average touch interaction per participant ± sd	335.72 ± 225.95	301.17 ± 195.46

4.5 Feature Extraction

From the touch interactions and the inertial motion sensors of the phone, we extracted a vector of features that describe the child's interaction with the mobile phone. In addition, we selected features explored in mobile touch interactions, focusing on aspects related to the geometry of touch interaction [8, 53, 87], performance [8], and movement produced in the phone [18] (For more details, see supplementary Table A). The consecutive data from each gesture were transformed into a single feature vector, which includes 13 features derived from the internal data of the phone, the screen, and the interaction of the children (e.g., force, accelerometer, gyroscope). For each feature, we calculated statistical values (i.e., mean, standard deviation). We categorized the features into two groups; (1) tilt: describes how children hold and rotate the phone. (2) touch: describes the screen space that children use to perform touch interactions and how children perform touch interactions over time.

To extract the features, we initially grouped the touch interactions by ID. We then calculated the features described in Appendix A for each touch interaction, obtaining statistical values to represent their distributions. Following this feature extraction process, we assigned labels to each touch interaction, categorizing them as ASD or NT.

4.6 Feature analysis

In order to understand how each feature distinguishes between children with ASD and NT, and identify digital markers of ASD, we divided this analysis into two parts.

The first part of our approach involves reducing features by selecting the most relevant ones to build a touch interaction classification model. The goal is to identify features that can improve the model's accuracy and effectiveness. According to the literature, focusing on the most relevant features may aid in uncovering digital markers in machine learning and filter the redundant and\or irrelevant features that could negatively impact the model performance [52]. For this work, we used ANOVA F-test feature selection, which reduces overfitting since the results are independent/separate from the classifier algorithm; in this manner, the selected feature set is more general and not fine-tuned to any specific classifier [80]. The method calculated the ratio of variance between groups and within a group for each feature; greater value of F-score means that the distances within the groups are less and distances between the groups are more. The features were ranked based on higher values of F-score. It's considered best practice to evaluate model configurations on classification tasks using repeated stratified k-fold cross-validation [22]. Therefore, we employed a Grid SearchCV[2] to systematically test various numbers of selected features and determine which configuration yielded the best-performing model.

The second part of our approach involves comparing the interactions of ASD and NT children using the selected features, with the goal of identifying distinct patterns and digital markers. We first conducted a Shapiro test to assess the normality of our data, which confirmed its non-normal distribution. Group differences in age, sex, and features between children with ASD and NT were assessed using a two-sided Mann-Whitney-U test with a significance at the 0.5 level. We calculated the effect size *(d)* using Cohen's D for each relevant features. Additionally, we used Spearman correlation (r) to examine the association between demographic features (age, sex) and game performance, and the association between the clinical tests administered during recruitment and game performance. We manually grouped the relevant features to define digital markers, carefully selecting and categorizing them based on their significance and relevance to create distinct and meaningful markers.

4.7 Modeling

For the classification task, we utilized 10,541 touch interactions from 36 NT children and 6,043 touch interactions from 14 children with ASD. These interactions were crucial for training and evaluating our model's performance in distinguishing between the two groups (i.e., interactions from NT vs interaction from ASD) based on their touch interactions (Table 2

4.7.1 Classification Algorithm. We recognize the importance of identifying subgroups of ASD [101], however, as an initial step in addressing this problem's complexity, we focused our study on a supervised binary classification task

We defined the binary classification task using a logistic regression model to distinguish the touch interactions of children with ASD from NT children.

We used scikit-learn [75], a library for machine learning in Python, which provides both supervised and unsupervised learning algorithms. Furthermore, our main goal was to evaluate the impact of feature selection on model performance. To do this, we trained two models: one using all available features to establish a baseline, and another using only the features selected in the previous stage. This comparison allowed us to assess the effectiveness of our feature selection process in improving model accuracy and efficiency.

4.7.2 Validation and performance evaluation. To validate our results, we employed 10-fold cross-validation, which is known to provide a reliable estimate of model performance [20]. However, when a dataset includes

[2]https://scikit-learn.org/stable/modules/generated/sklearn.model$_selection.GridSearchCV.html$

multiple measurements from the same participant, using Group K-fold cross-validation[3] is recommended to avoid overfitting and assess the model's generalizability, considering individual variability [89]. Group K-Fold cross-validation prevents multiple touch interactions from the same child from being split between the training and validation or test sets. In our case, we set K equal to the number of participants, ensuring that each iteration designated one of the k groups as test data while using the remaining (k-1) groups as training data. This method provided a more accurate evaluation of our model's performance by accounting for the inherent variability between participants.

To evaluate the performance of the model, we selected standard evaluation metrics including precision, recall, F-score (F1), the area under the curve (AUC), and classification accuracy (CA). Given that our research aims to identify touch interactions of ASD, we wanted to avoid type 1 error; thus, we prioritize the metrics of precision and recall for model comparison.

5 RESULTS

5.1 Comparisons of interactions in children with ASD versus NT

There were no statistical significance differences in age (*p*=0.13; two-sided Mann-Whitney test) between NT (N=36 children) and ASD (N=19 children) children, indicating a similar balanced distribution of age. Children with ASD (M= 301, SD= 19.05) and NT (M= 335, SD= 22.5) did not statistically differ in terms of the mean number of touches (p=0,88;two-sided Mann Whitney test) indicating similar levels of overall engagement with the game.

5.2 Correlations between touch interactions and clinical scores

We examined the correlations between total touch interactions of all children — both ASD and NT -and the AQ-10, SSP, ASQ scores (Figure 6) with the 14 relevant markers identified during the feature analysis. The AQ-10 was found to be slight positively correlated with: touch vibration (r=0.06, p-value<0.05), with the tilt direction along x-axis (r=0.02, p-value<0.05), and along y-axis (r=0.13, p-value<0.05), with the touch velocity (r=0.07, p-value<0.05); and negatively correlated with the touch size (r=-0.10, p-value<0.05), and horizontal touch distance to the center (r=-0.03, p-value<0.05) although the magnitude of the negative correlation was small.

The SSP was found to be slight positively correlated with tilt direction along y-axis (r= -0.15, p-value<0.05), touch size (r=-0.07, p-value<0.05), horizontal touch distance to the center (r= -0.03, p-value<0.05), and touch velocity (r=0.05, p-value<0.05); and negatively correlated with touch vibration (r= -0.11, p-value<0.05), tilt direction along x-axis (r= -0.01, p-value<0.05), and touch size (r=-0.06, p-value<0.05).

The ASQ was found to be slight positively correlated with touch vibration (r= 0.10, p-value<0.05), tilt direction along y-axis (r=-0.02, p-value<0.05), tilt velocity (r=0.10, p-value<0.05), touch velocity (r=0.07, p-value<0.05); and negatively correlated with touch size (r=-0.21, p-value<0.05), horizontal touch distance to the center (r=-0.09, p-value<0.05).

[3] https://scikit-learn.org/stable/modules/generated/sklearn.model$_selection.GroupKFold.html$

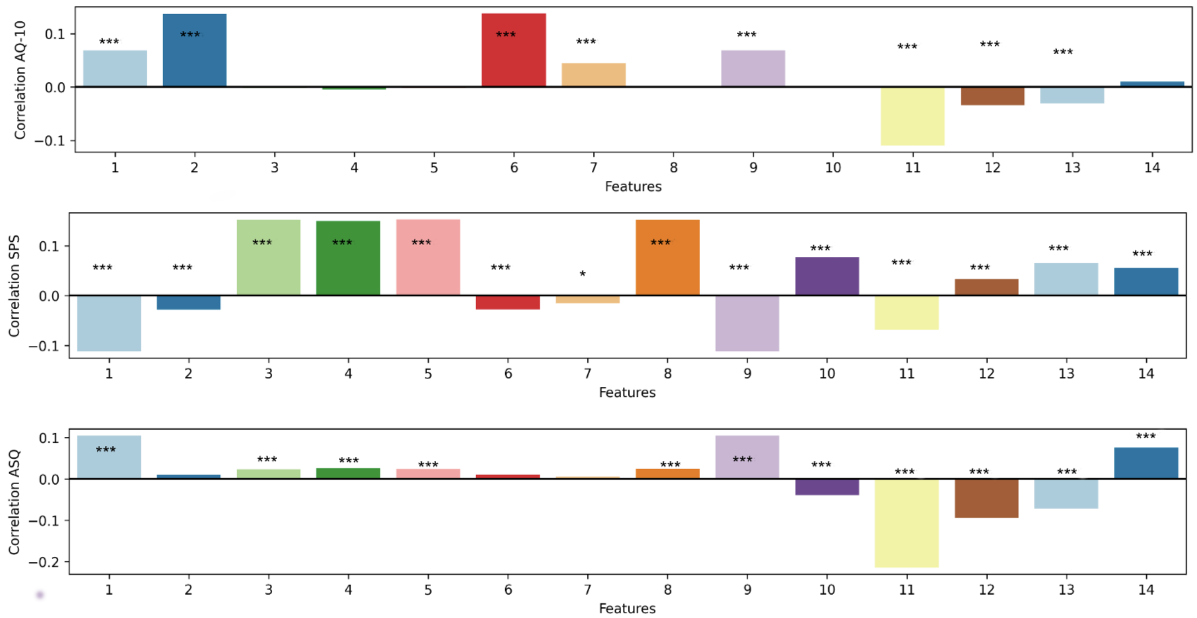


Fig. 6. Correlations between motor performance and clinical scores. (1) Final flick along X-axis. (2) Average flick along X-axis. (3) Average flick along Y-axis (4) Initial flick along Y-axis (5) Final flick along Y-axis (6) Max flick along Y-axis (7) Tilt (8) Angular velocity (9) Total acelerario (10) Average Radius (11) Std Radius (12) Distance to the center (13) Final touch in x (14) Average speed. *p<0.05; **p<0.01; ***p<0.001;

5.3 Digital Markers

As previously noted, our feature analysis narrowed the scope to 14 features that were most pertinent in differentiating touch interactions between ASD and NT groups. Further analysis revealed three characteristics that showed significant differences between ASD and NT children (see Figure 7). These three features emerged as the most critical in our study (see Table 3).

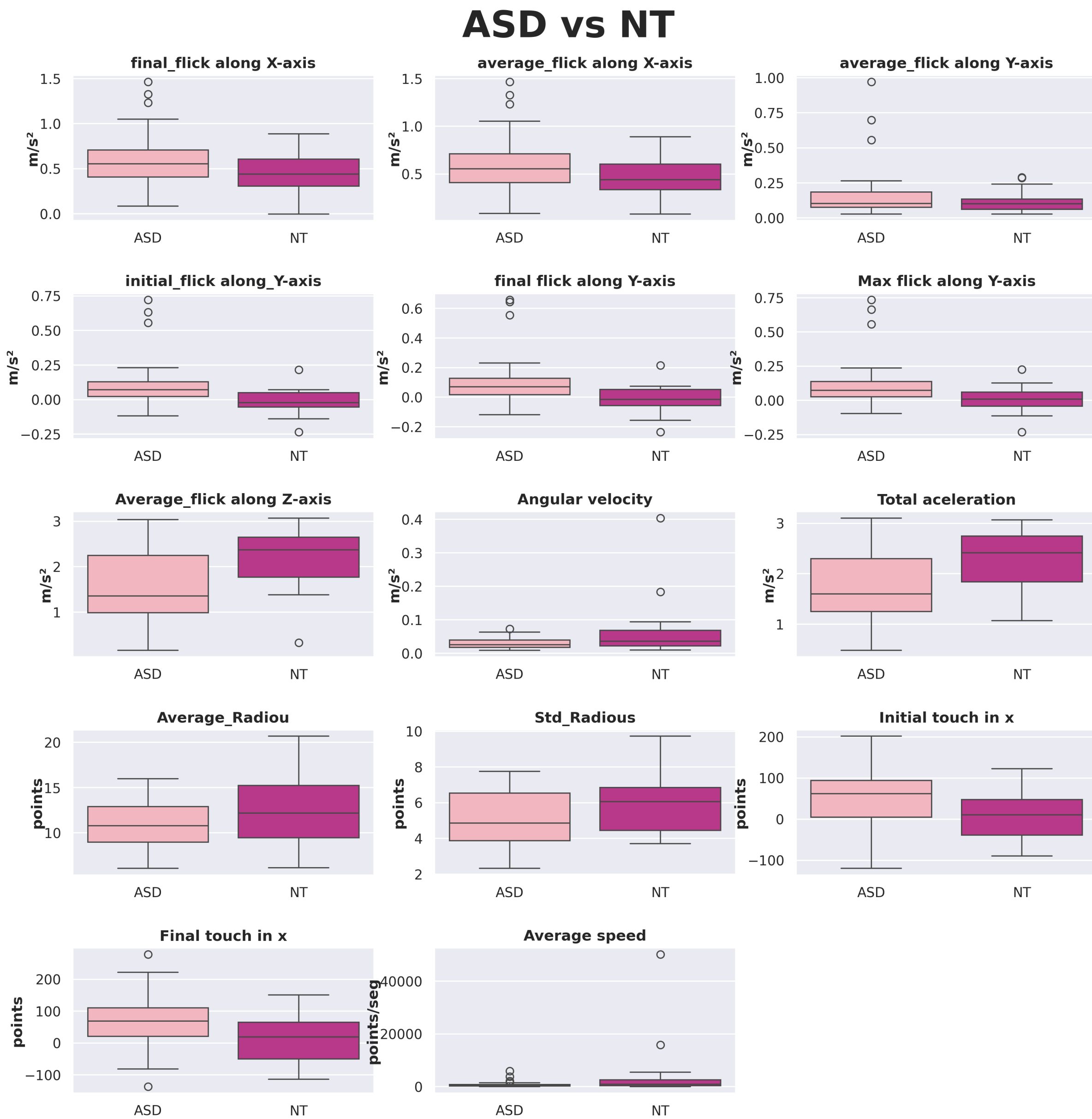


Fig. 7. Box plot of the features that best distinguish children with ASD and NT children. Box plots show median values for each population.

Table 3. Features and digital markers extracted from the touch interactions. The table shows the digital markers that best distinguish children with ASD from NT and from other neurodevelopmental disorders

Group	**Digital Marker**	**Description**	**Features**
Tilt	Tilt direction	The mobile phone is accelerated by tilting movement in the desired direction (Tilting). From the internal acceleration sensors, we compute changes different measurements by rotating the phone. The phone could be tilting to the left or right (horizontal rotation), up or down (vertical rotation), and back or forward (deep rotation).	Average flick along Z-axis
Touch	Total acceleration	Acceleration of the vibration produced on the phone when a child performs a touch interaction.	Vibration wave total acceleration
	Horizontal touch Distance to the center	Horizontal distance (x-axis) in points from the initial and end touch and the center of the phone display.	Initial touch in x.

5.3.1 Tilt. Although all participants used the mobile phone with a phone ring holder to reduce movement and make it more comfortable to use, touch interactions and the way they positioned the phone in their hands influenced the tilt direction. The tilt on the Z-axis shows that children with ASD (2.19±0.68) on average tilt the phone more forward/backward than NT children (1.49±0.67, d = 0.9). Figure 7 shows that in the case of children with ASD, approximately 75% of interactions are between 2 and 3 m/s^2, while interactions for NT children are more scattered.

5.3.2 Touch. Although all participants used the same mobile phone and completed the same game, there were also differences in touch-related features. For instance, the total acceleration shows that on average, touch interactions of children with ASD (2.19±0.68) result in higher acceleration compared to NT children (1.49±0.0.8, d = 0.85). Figure 7 illustrates how approximately 75% of interactions by children with ASD fall between 2 and 3 m/s2, whereas 75% of interactions by typically developing children are below 2.5 m/s2.

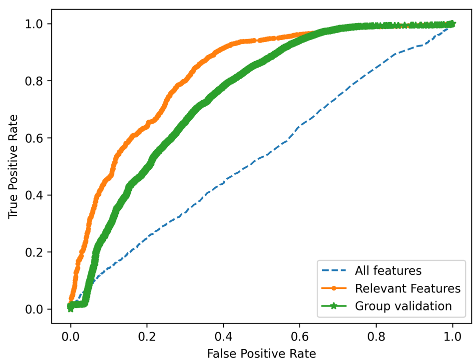
The horizontal distance to the center of the screen shows that, on average, children with ASD (5.04±60.75) tend to make touch interactions closer to the center compared to typically developing children (51.79±68.22, d = 0.7).

5.4 Touch classification performance

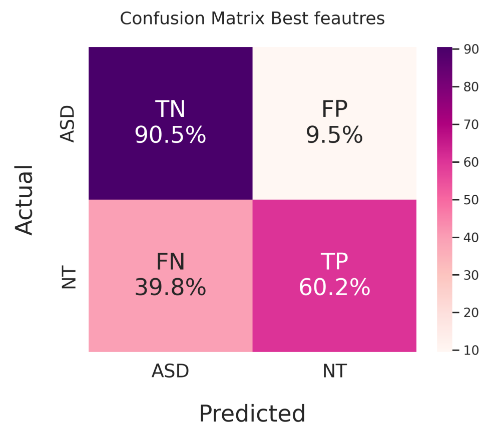
As described in 4.7 Modeling, we built two classification models, one with all features captured and another with the top features identified from the previous step. As shown in Figure 8, through the utilization of the most relevant features, our model achieves a precision of 79%, demonstrating its efficacy in accurately discerning children with ASD while mitigating false positives. Furthermore, with a recall of 80%, our model identifies most touch interactions of children with ASD in the dataset. Overall, we successfully constructed a model capable of accurately classifying touch interactions.

The group validation shows similar results, we reached a precision of 76%-79% and a recall of 80%-87%. (Table 4). This performance is consistent with the individual touch interaction validation, demonstrating the model's efficacy in accurately discerning children with ASD and mitigating false positives across different datasets.

The model demonstrated the ability to classify touch interactions with high precision and recall, showcasing its effectiveness in distinguishing between touch interactions of ASD and NT children.



(a) ROCs and AUCs values were derived from logistic regression classifiers. These classifiers compared the performance of a model incorporating all extracted features to another model that included only the most relevant features for distinguishing between children with ASD and NT children.



(b) Confusion Matrix depicting the classification performance of a predictive model distinguishing between ASD and NT children, with True Negative (TN) rate of 90.5%, False Positive (FP) rate of 9.5%, False Negative (FN) rate of 39.8%, and True Positive (TP) rate of 60.2%

Fig. 8. The figure illustrates the model efficacy through a visual representation of the ROC curve and confusion matrix.

Cross validation	Features	Accuracy	Precision	Recall	F1
10-fold	All features	60%	63%	89%	74%
10-fold	Relevant features	77%	79%	87%	83%
Group validation	Relevant features	72%	76%	80%	78%

Table 4. Performance metrics for classification models evaluated using different cross-validation methods and feature sets. The table compares accuracy, precision, recall, and F1 scores for models using all features with 10-fold cross-validation, relevant features with 10-fold cross-validation, and relevant features with group validation.*

6 DISCUSSION

6.1 Touch interactions differences as digital markers

Our results show that the mobile haptic game we developed can effectively promote touch interactions among neurodiverse children and capture haptic data with sufficient detail. This addresses the question: *Can haptic mobile games be effectively used to collect touch interactions from children?* The data collected is useful for uncovering differences in touch interactions among children.

Through an extensive feature analysis, we identified a total of three potential ASD digital markers that could be used as a starting point for analyzing children's touch interactions. Those markers can be categorized into two distinct groups: tilt and touch.

Tilt. Although all participants used the mobile phone with a phone ring holder, small movements over time were captured by the phone. Small movements naturally occur when performing gestures on a phone that is not fully static. Our results show that these small movements can be analyzed and used to distinguish touch patterns for individuals with neurological disorders. In our study, children with ASD exhibited more pronounced patterns of moving the phone toward and away from themselves. This could be partially explained because children with ASD might either seek intense sensory stimulation being received from the vibrotactile feedback provided by *Feel and Touch* or have engaged in stereotyped behavior. Indeed, research has reported similar findings regarding how motor patterns of children with ASD influence their manipulation of mobile devices [9, 82], though previous studies primarily concentrated on tablet usage and did not use haptic stimulation. These results suggest that the exploration of hand movements and the incorporation of 3D gestures could reveal other unknown touch differences beyond those we can uncover from tracking 2D touch interactions. Further research needs to explore the design space for refining the development of *Feel and Touch* or similar tracking applications to incorporate interactions based on hand movements, such as 3D gestures, and their mapping to innovative vibrotactile patterns. This approach could provide additional insights into the hand movements of children with ASD and how vibrotactile patterns may influence such touch interactions.

Touch. Although all participants used the same mobile phone and there were no differences in the screen size, there were differences in the space used by children with ASD to perform touch interactions. The literature has found similar results by using mobile devices with a larger screen, like tablets [9, 76]. In addition to the space touched we explored the total acceleration produced by the touch interactions, this digital marker has previously been explored in other contexts, such as analyzing the total acceleration of adults to be used as a unique ID to unblock mobile phones [18]; but has not been used in the screening of ASD. Our results show that there are differences in how ASD and NT children perform touch interactions. The total acceleration produced by children is a prominent feature that distinguishes children with ASD from NT children. This digital marker had a large effect size (d = .85) which means that there is a significant difference between the total acceleration produced by children with ASD, this result may be related to the vibrotactile patterns provided by *Feel and Touch* and the sensory difficulties presented by children with ASD [34].

While research has shown that children with ASD have difficulties to process vibrations [38, 64]; more explicit studies are needed to fully understand how vibrotactile patterns affect the touch interactions of children with ASD and what component of the vibrotactile patterns is more important to distinguish between children with ASD and NT. To our knowledge, little research has been conducted about the use of touch vibration produced to distinguish children with ASD. Touch-based digital markers could also be related to sensory-motor-related impairments [**?**] and differences in visual processing [72] of children with ASD. Our findings align with existing research on digital markers of ASD that focus on touch interactions [9, 76].

Further exploration is required to investigate if there are touch interaction behavior patterns that can also signal differences between children with ASD and NT.

6.2 Potential as an innovative screening tool for ASD

The widespread availability and portability of smartphones present a unique opportunity for deploying screening tools across diverse demographics, including those in remote or underserved areas [99]. Utilizing smartphones for data collection and analysis can alleviate some burdens on healthcare systems [16]. Traditional screening methods often require substantial resources and may be limited by geographic or socioeconomic factors. A smartphone-based screening tool offers a cost-effective solution that is both scalable and accessible, reducing the need for extensive infrastructure and allowing for broader reach [59]. The integration of such technology could enhance screening efficiency and reduce costs, making early detection and ongoing monitoring more feasible for a larger population. Building on this potential, our study explored leveraging touch interaction data to develop a classification model designed to distinguish the touch interactions of children with ASD from those of NT.

6.2.1 Developing a Classification Model and Integrating It into a Mobile App for Early . Our study explored the potential of leveraging touch interaction data to develop a classification model designed to distinguish the touch interactions of children with ASD from those of NT children.Previous research has highlighted the importance of touch interactions in understanding behavioral and developmental differences in children with ASD [9, 76]. We constructed a classification model with promising precision and recall metrics, indicating its effectiveness in accurately distinguishing touch interactions of ASD from NT. This model can be integrated into the *Feel and Touc*h mobile app, enabling seamless and continuous monitoring of touch interaction data. It can provide immediate feedback to caregivers, guiding them to seek further diagnostic evaluation and confirmation from healthcare professionals. It is important to note that our approach does not promote excessive smartphone usage among children. Rather, it is intended as a support tool to aid in ASD screening, used in a controlled and minimal manner to complement existing diagnostic practices. The goal is to enhance early detection without compromising healthy development and ensuring that technology serves as an adjunct to, rather than a replacement for, traditional evaluation methods.

6.2.2 Addressing Challenges and Enhancing Model Performance. Despite these promising aspects, several challenges must be addressed before widespread implementation can be achieved. Our model's high recall compared to precision indicates a higher rate of false positives, which could lead to unnecessary concern among parents and caregivers. This issue underscores the importance of managing uncertainty effectively to prevent undue alarm. Strategies to address this include refining the model to balance sensitivity and specificity. Sensitivity measures the model's ability to correctly identify true positives, while specificity assesses its ability to correctly identify true negatives [5, 39]. Improving this balance is essential for reducing false positives and enhancing the model's overall reliability. Understanding the relationship between digital markers and specific screening assessment scores is crucial for refining the model and integrating it into existing diagnostic protocols. Further studies should focus on validating the model's effectiveness in real-world settings.

6.2.3 Clinical Decision-Making and Model Integration. The role of this model in clinical decision-making requires further exploration. While it can predict the class of each touch interaction, additional research is needed to determine the optimal amount of data required and the appropriate thresholds for referring children to specialists. Preliminary findings suggest that an average of 329 touch interactions can successfully identify about 85% of children needing further assessment. However, it is essential to refine these thresholds and validate their accuracy to improve the early identification of ASD. Moreover, enabling specialists to adjust the tool's sensitivity and providing clear indications of its confidence levels are critical for managing uncertainty. Transparent communication about the model's predictions and confidence can help caregivers make more informed decisions, reducing unnecessary anxiety [84]. Understanding the likelihood of true positives and negatives allows parents to seek further evaluation when appropriate.

6.3 Unlocking the sensory frontier through mobile sensing and haptic interfaces

There is significant untapped potential in developing and leveraging accessible technology for tracking touch interactions and hand movements to assist in the screening and monitoring of children with neurodevelopmental disorders [9, 76]. Even though we followed a user-centered approach to design *Feel and Touch*, there remain numerous research questions concerning user engagement and gamification to sustain users' interest when designing similar applications. Key inquiries include determining the appropriate incentives to motivate users to collect and share their touch interactions data [103], and drawing insights from the field of Personal Informatics to enhance user engagement and ensure long-term usage is crucial [69]. Furthermore, investigating methods to tailor the application to individual user needs and preferences, considering factors such as age, sensory sensitivities, and developmental stage, can enhance its effectiveness and user experience. Moreover, ongoing collaboration with clinicians, educators, and caregivers is essential to ensure that the technology meets the diverse needs of its users and aligns with clinical objectives. By addressing research questions related to data sharing and user engagement, we can further optimize the utility and impact of technology-based tools like *Feel and Touch* in supporting the assessment and intervention for children with neurodevelopmental disorders.

Mobile sensing offers a promising avenue for uncovering digital markers in healthcare, presenting a paradigm shift in how we monitor and understand various health conditions [13]. By leveraging the sensors embedded in smartphones, such as accelerometers, gyroscopes, GPS, cameras, and microphones, researchers can collect a diverse array of data in real-time and in naturalistic settings . This continuous and unobtrusive monitoring enables the capture of nuanced behavioral, physiological, and environmental signals that may serve as digital markers for health and disease. Importantly, mobile sensing provides a holistic view of individuals' daily lives, capturing patterns and trends that may go unnoticed in traditional clinical settings [48]. These digital markers have the potential to revolutionize healthcare by enabling early detection, personalized interventions, and remote monitoring of various conditions, including mental health disorders, neurological conditions, cardiovascular diseases, and respiratory illnesses [31]. However, challenges such as data privacy, security, validation, and integration into existing healthcare systems need to be addressed to fully realize the potential of mobile sensing in uncovering digital markers for healthcare. Nonetheless, the prospect of harnessing ubiquitous smartphones as powerful health monitoring tools holds immense promise for improving patient outcomes and advancing our understanding of health and disease.

Moreover, haptic interfaces hold immense promise as a versatile tool for advancing our understanding of tactile processing differences and paving the way for innovative interventions in the realm of neurodevelopmental disorders. By harnessing the power of tactile feedback, these interfaces present an opportunity to delve deeper into the nuances of sensory processing and tactile sensitivity among individuals, particularly those with neurodevelopmental disorders like ASD. Our prototype was limited in the sense of relying on the motors available in a smartphone, which restricted control over the characteristics of the motor vibration. The use of multiple vibration motors could enable richer and more complex vibrotactile patterns, facilitating developers in creating diverse experiences. Without the ability to adjust vibration levels, the application may lack adaptability to the individual preferences of children with ASD, who often exhibit diverse tactile sensitivities.

Through carefully designed haptic feedback patterns, researchers can elucidate how variations in vibrotactile stimulation influence the sensory experiences and behavioral responses of individuals across different populations. Indeed, numerous research projects are underway to investigate methods for altering surfaces using vibrotactile patterns to simulate textures [70] such as roughness, adhesion, sharpness, and more. These efforts aim to replicate tactile sensations through haptic feedback, offering users a multisensory experience that enhances immersion and interaction in virtual environments. By leveraging advancements in haptic technology, researchers are exploring innovative ways to mimic real-world textures and sensations, thereby expanding the possibilities for applications across various domains, including gaming [93], virtual reality [102], and assistive technology [51]. These developments not only contribute to the advancement of haptic interfaces but also hold promise for revolutionizing touch interactions. Furthermore, exploring the interplay between haptic interfaces and sensory integration processes can shed light on potential therapeutic interventions aimed at modulating sensory processing and improving sensory integration abilities in clinical settings.

6.4 Ethical considerations

Data privacy is a significant concern in health technology applications [14, 44], while we are recording touch interactions, no sensitive information about children is being collected. The data is anonymized using an ID, and we strictly record interactions within the Feel and Touch app. We do not access or record any information that could potentially reveal sensitive data, such as passwords. Furthermore, if a child closes the game or sends it to the background, Feel and Touch immediately ceases recording. At this point, the data is temporarily stored in the phone's internal storage. However, it is important to acknowledge that future work will need to address encryption techniques to further safeguard this data and ensure comprehensive protection against unauthorized access.

The literature emphasizes the importance of providing users with clear explanations about the results, avoiding the use of machine learning models to black boxes [84]. By incorporating digital markers, we aim to offer transparency and understanding of the results. For future real-world applications, it is crucial that clinicians receive not only the classification results but also the digital markers to comprehend these outcomes fully. We need to collaborate closely with experts to determine how best to convey this information, define appropriate thresholds, and ensure the practical and ethical application of these models in clinical settings.

It is important to highlight that we are not attempting to replace the diagnosis made by an expert. The literature has shown that the use of machine learning applications must be taken as a complement to the diagnostic process to avoid misuse [100]. Machine learning models can assist in early detection and provide valuable insights [100], but they cannot replace the nuanced judgment of a trained clinician. Ethically, it is essential to maintain the clinician's role in the diagnostic process to ensure patient safety and uphold the integrity of medical practice.

One ethical issue in applications such as the one presented in this study is the risk of stakeholders misinterpreting or manipulating results. To address this, it is essential to establish guidelines for interpreting results and ensure clear communication with parents. This includes discussing the potential for false positives and false negatives, the confidence level in the model's predictions, and the appropriate actions to take based on the results.

By addressing these ethical considerations and potential risks proactively, we can ensure that the deployment of this screening tool is both responsible and effective, ultimately contributing to better outcomes for children with ASD and their families.

6.5 ASD diagnostic in Latin America

Cultural and socio-economical factors play a significant role in how ASD is identified and understood in different regions [11]. Cultural dynamics significantly impact both the timing and accuracy of ASD diagnoses, as well as the availability and accessibility of intervention services [33]. In many Latin American cultures, there is often a lack of awareness or understanding of ASD among the public and healthcare professionals, which can delay the recognition of symptoms and subsequently postpone diagnosis [68]. Cultural beliefs and stigmas may lead to misinterpretation of developmental delays as mere behavioral issues, thereby preventing early identification and intervention [73]. Additionally, varying cultural attitudes toward mental health and developmental disorders can influence how symptoms are perceived by parents, educators, and healthcare providers, potentially leading to underreporting or misdiagnosis [73]. Furthermore, cultural stigma and misconceptions about developmental disorders can also affect the willingness of parents to seek professional help. In many Latin American communities, there may be a reluctance to acknowledge or address developmental issues due to fear of social ostracism or misunderstanding of the condition [67].

Moreover, the availability and accessibility of intervention services are heavily influenced by cultural and socioeconomic factors. Differences in healthcare infrastructure and access to specialized services can impact the consistency and accuracy of diagnoses and can restrict access to specialized ASD services, which are often concentrated in urban areas, leaving rural populations underserved [17]. Cultural barriers, such as mistrust of medical professionals or preference for traditional healing practices, may also impact the willingness of families to engage with formal healthcare services. This situation is compounded by socioeconomic disparities that can hinder families' ability to afford and access necessary interventions.

By focusing on this underrepresented region, our study not only addresses critical gaps in current research, regarding studies from these countries but also provides valuable insights that can inform and improve ASD diagnosis and perception in Latin America.

7 LIMITATIONS

The main limitation of our work, like that of others addressing similar research questions, is the sample size and the fact that we conducted the study in only one clinic and one school in central Mexico. Consequently, like many studies conducted in real-world settings, our dataset is imbalanced. It is interesting to note that the sample collected reflect the inherent difficulties in recruiting children with ASD in Mexico, especially as many Mexican children remain undiagnosed or receive diagnosis after the age of 5 [43]. However, our chosen sample size strikes a balance between precision and feasibility, enabling a thorough exploration of the research questions of this work. Past studies investigating machine learning for identifying digital markers of individuals with neurodevelopmental disorders have demonstrated that sample sizes ranging from as low as 11 [98] to as high as 45 participants ensure adequate statistical power and representativeness [35]. This body of work strongly advocates that a small sample can suffice for a study when the dataset maintains high-quality standards. By adhering to these insights, our study attains the requisite statistical power to discern meaningful effects and furnish dependable insights within the targeted domain. Expanding the sample of children diagnosed with ASD could provide more information and improve the accuracy of the current model.

Another limitation of our dataset is that by the size we were unable to explore a multi classification task. By moving beyond binary classification and embracing the complexity of the spectrum, we can make significant strides in meeting the diverse needs of the ASD community [101]. This approach will enable us to develop more personalized and effective diagnostic tools, which can identify subtle differences and specific characteristics within subgroups of ASD. It will also facilitate the creation of tailored intervention strategies, ensuring that each individual receives support that is precisely suited to their unique profile. To improve the robustness and applicability of our model, future research should focus on collecting larger, more diverse datasets. Such datasets should include a wider range of participants, representing various ages, genders, ethnicities, and comorbid conditions. By doing so, we can develop more sophisticated and nuanced classification systems that better reflect the spectrum nature of ASD. This would allow for more accurate identification of subgroups within the spectrum, leading to tailored interventions and support strategies that address the specific needs of individuals. Additionally, employing unsupervised learning techniques and clustering methods could help uncover hidden patterns and relationships within the data, providing deeper insights into the heterogeneity of ASD

One of the limitations of the *Feel and Touch* game is its exclusive compatibility with iOS devices, which restricts its accessibility to a broader audience that could potentially benefit from this tool. Additionally, iOS devices feature only a single vibration motor, imposing constraints on the range of vibration intensity levels that can be utilized. These limitations may impede the comprehensive exploration of crucial aspects of tactile interactions in children with ASD. For instance, the limited capacity to vary vibration intensity may hinder the assessment of the child's ability to discern the precise location of haptic feedback, potentially limiting the depth of insights gained into the tactile processing abilities of these children. Consequently, while the *Feel and Touch* game offers valuable insights into tactile interactions, its platform compatibility and hardware limitations pose challenges in fully capturing the nuances of tactile processing in children with ASD. Addressing these limitations through platform diversification and enhanced vibration control mechanisms could significantly enhance the utility and effectiveness of the *Feel and Touch* game as a diagnostic and therapeutic tool in ASD research and intervention.

The identification of digital markers for children with ASD has been a persistent endeavor in the field. While many studies have utilized environmental sensors and mobile devices to collect data and extract features, few have tapped into the full potential of mobile technology, particularly haptic interfaces, to gather touch interactions. Our study introduces an innovative approach by exploring the design and deployment of a mobile haptic game named F*eel and Touch*. By continuing to explore more effective methods for extracting digital markers, we aim to enrich the literature and contribute to developing a tactile phenotype for ASD, which could enhance screening processes.

Additionally, the intervention was conducted in two distinct locations, which may have introduced environmental factors affecting the results. To address this, the research team standardized the protocol, used identical equipment, and had a single researcher deliver the intervention. However, there are uncontrollable variables might limit the generalizability of the findings across other settings and populations, and should be considered when interpreting the results.

8 CONCLUSION

In this paper, we described a study aimed at measuring touch interactions for children with ASD and NT children. The design of *Feel and Touch* and results from its usage demonstrated the feasibility of leveraging the haptic capabilities of smartphones to collect touch interaction data that can uncover differences in the way children with ASD interact with a smartphone. Our research addressed several key questions: We confirmed that haptic mobile games like *Feel and Touch* can effectively capture detailed touch interactions from children. We also identified three digital markers, categorized into touch and tilt. These markers have been used to build models with promising precision and recall, suggesting their potential for accurate classification of touch interactions. Furthermore, we found that alterations in tactile processing in children with ASD can be measured through their interactions with haptic interfaces, as evidenced by the distinct touch patterns and phone movements observed.

These findings suggest that digital markers based on touch interactions could lead to the development of an innovative screening tool that could potentially pave the way for more accessible and cost-effective solutions that empower parents and caregivers to seek timely support and early intervention for their children's well-being, as well as expand the awareness of motor differences for children with ASD. Significantly, this study is among the first to collect touch interaction data from Mexican children, broadening the population scope and adding valuable context underrepresented in the field. It is imperative to support this line of work and continue exploring the potential of touch interactions in the screening and monitoring of neurological disorders. This study is also one of the first to exemplify the use of haptic interfaces in smartphones to collect touch interactions of children with ASD.

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A TABLE OF SUPPLEMENTARY DATA: DIGITAL MARKERS AND FEATURES

Table 5. Detailed Description of Digital Markers Used in Touch Interaction Analysis

Feature	**Description**
x_neg_count	Counts the negative values from the acceleration.
y_neg_count	Counts the negative values for the y-axis from the acceleration.
z_neg_count	Counts the negative values for the z-axis from the acceleration.

Feature	Description
x_pos_count	Counts the positive values from the acceleration.
y_pos_count	Counts the positive values for the y-axis from the acceleration.
z_pos_count	Counts the positive values for the z-axis from the acceleration.
variability	The cumulative sum of the Euclidean distance between underlying points [8].
area	Total area of the tactile interaction.
Bounding box	Two two-dimensional vectors (x, y) representing the origin and the end of the box around each tactile interaction.
Angle of the bounding box,	The angle formed by the diagonal of the bounding box [88].
Diagonal of the bounding box	Length of the bounding box diagonal [88].
avgSpeed	The speed at which a tactile interaction occurs. [8]
aspectRatio	Proportional relationship between the width and height of the bounding box. [53]
density	Relationship between the length of the tactile interaction and the distance .
Distance	Distance between the first and the last point of the tactile interaction in points [88].
total acceleration	Total acceleration of the vibration produced by the children's interaction. [18]
angular	The speed at which the mobile phone rotates [18].
production-time	Duration of the touch interaction.
Game performance	Total number of tactile interactions.
x_ini	Point where the touch interaction starts in x.
x_fin	Point where the touch interaction ends in x.
x_mean, x_max, x_min, x_std	Statistical measures (mean, maximum, minimum, standard deviation) of x-coordinate values during the interaction.
y_ini	Point where the touch interaction starts in y.
y_fin	Point where the touch interaction ends in y.
y_mean, y_max, y_min, y_std	Statistical measures of y-coordinate values during the interaction.
acX_ini	Accelerometer initial x-value.
acX_fin	Accelerometer final x-value.
acX_mean	Average x-value recorded by the accelerometer.
acX_max	Maximum x-value recorded by the accelerometer.
acX_min	Minimum x-value recorded by the accelerometer.
acX_std	Standard deviation of the accelerometer x-values.
acY_ini	Initial accelerometer y-value.
acY_fin	Final accelerometer y-value.
acY_mean	Average y-value recorded by the accelerometer.
acY_max	Maximum y-value recorded by the accelerometer.
acY_min	Minimum y-value recorded by the accelerometer.
acY_std	Standard deviation of the accelerometer y-values.
acZ_ini	Initial accelerometer z-value.
acZ_fin	Final accelerometer z-value.
acZ_mean	Average z-value recorded by the accelerometer.
acZ_max	Maximum z-value recorded by the accelerometer.
acZ_min	Minimum z-value recorded by the accelerometer.
acZ_std	Standard deviation of the accelerometer z-values.
gX_ini	Initial gyroscope x-value.
gX_fin	Final gyroscope x-value.

Feature	**Description**
gX_mean	Average x-value recorded by the gyroscope.
gX_max	Maximum x-value recorded by the gyroscope.
gX_min	Minimum x-value recorded by the gyroscope.
gX_std	Standard deviation of the gyroscope x-values.
gY_ini	Initial gyroscope y-value.
gY_fin	Final gyroscope y-value.
gY_mean	Average y-value recorded by the gyroscope.
gY_max	Maximum y-value recorded by the gyroscope.
gY_min	Minimum y-value recorded by the gyroscope.
gY_std	Standard deviation of the gyroscope y-values.
gZ_ini	Initial gyroscope z-value.
gZ_fin	Final gyroscope z-value.
gZ_mean	Average z-value recorded by the gyroscope.
gZ_max	Maximum z-value recorded by the gyroscope.
gZ_min	Minimum z-value recorded by the gyroscope.
gZ_std	Standard deviation of the gyroscope z-values.
mRadius_ini	Initial radius of the tactile interaction as provided by iOS.
mRadius_fin	Final radius of the tactile interaction as provided by iOS.
mRadius_mean	Average radius during the tactile interaction.
mRadius_max	Maximum radius recorded during the tactile interaction.
mRadius_min	Minimum radius recorded during the tactile interaction.
mRadius_std	Standard deviation of the radius values during the interaction.
force_ini	Initial force of the touch interaction provided by iOS.
force_fin	Final force of the touch interaction.
force_mean	Average force during the touch interaction.
force_max	Maximum force recorded during the touch interaction.
force_min	Minimum force recorded during the touch interaction.
force_std	Standard deviation of the force values during the interaction.
reactionTime	Time between the start of the vibration and the child's response.
population	Category of participant, ASD or NT. [8]
time	Time when the touch interaction starts.
ID_participant	ID of the participant.
Cosine	Cosine of the angle of the diagonal of the bounding box. [8]
Sine	Sine of the angle of the diagonal of the bounding box.[8]
instruction	Type of instruction given during the interaction. [8]

B TABLE OF DIGITAL MARKERS RELATED WORK

		Digital Markers					Participants			Precision (%)
		G	V	M	T	O	ASD	NT	Other	
Digital markers based on sensing										
Devices in the environment	Carette et al., 2018	X					18*	18*		95
	Yaneva, 2018	X					18*	18*		75
	Nakano et al., 2010	X					25	25		/
	Hashemi et al., 2012	X					1			/
	Santos et al,2013		X				20	23		97.7
	Xu et al., 2009		X				34	30		90
	Dongxin et al.,2009		X				34	76	30	90
	Deng et al., 2017		X							/
	Dai & Keshi, 2007		X							/
	Crippa et al., 2015			X			15	15		96.70
	Bidwell et al, 2014					X				93.3%
	Liu,et al., 2016	X					29	29		88.51%
	Vabalas,et al., 2019			X			24*	22*		71%
	Kanhirakadavath et al., 2022	X					219	328		91.38
	Banire et al., 2021	X					20	26		96.5
	Oliveira et al., 2021	X					76	30		93
	Yaneva et al., 2020	X					31	40		74
	Wan et al., 2019	X					37	37		83.8
	Briend et al., 2023		X				38	24		91
	Lyakso et a., 2022		X				95	150		60.2
	Boorse et al., 2019						62	40		/
	Cavallo et al., 2021			X			20	20		75
	Alcañiz-Raya et al., 2020			X			24	25		82.98
	Ardalan et al., 2019			X			39	23		89
Digital markers based on interaction										
Mobile devices	Vargas-Cuentas et al., 2017	X					8	23		98.5
	Gong et al., 2018		X				18	9	8	/
	Mahmoudi-Nejad et al., 2017					X	5	7		/
	Anzulewicz et al.,2016				X		37	45		93
	Chen et al., 2019						40	51		/
	Perochon et al., 2023	X			X		233	147		74
	Lu et al, 2019				X		37	45		/
	Rafique et al., 2019				X		22	22		91

Table 6. Table 1 The table shows related works on digital markers of ASD. It describes the type of digital marker studied in each work: Gaze (G), Voice (V), Motor Skills (M), Touch interactions (T), Others (O); the number and type of participants; and the accuracy achieved in classifying ASD and NT

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