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Automatic Assessment of Motor Impairments in Autism Spectrum Disorders: A Systematic Review

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Abstract Autism spectrum disorder (ASD) is mainly described as a disorder of communication and socialisation. However, motor abnormalities are also common in these individuals. New technologies may offer quantitative and automatic metrics to measure movement difficulties. We sought to identify computational methods in order to automatize the assessment of motor impairments in ASD. We systematically searched for the terms 'autism', 'movement', 'automatic', 'computational', and 'engineering' in IEEE (Institute of Electrical and Electronics Engineers), Medline and Scopus databases and reviewed the literature from inception to 2018. We included all articles discussing: (1) automatic assessment/new technologies, (2) motor behaviors, and (3) children with ASD. We excluded studies that included patient's or parent's reported outcomes as online questionnaires, that focused on computational models of movement, but also eye tracking, facial emotion or sleep. In total, we located 54 relevant articles that explored static and kinetic equilibrium, like posture, walking, fine motor skills, motor synchrony and movements during social interaction that can be impaired in individuals with autism. Several devices were used to capture relevant motor information such as cameras, 3D cameras, motion capture systems, accelerometers. Interestingly, since 2012, the number of

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studies increased dramatically as technologies became less invasive, more precise, and more affordable. Open-Source softwares have enabled the extraction of relevant data. In a few cases, these technologies have been implemented in serious games like "Pictogram Room", to measure the motor status and the progress of children with ASD. Movement computing opens new perspectives for patient assessment in ASD research, enabling precise characterizations in experimental and at-home settings, and a better understanding of the role that sensorimotor disturbances could play in the development of social cognition and ASD. These methods would likely enable researchers and clinicians to better distinguish ASD from other motors disorders while facilitating an improved monitoring of children's progress in more ecological settings (i.e. at home or school).

Keywords automatic · computational · autism spectrum disorders · clumsiness · movement · diagnosis

1 Background

Autism spectrum disorder (ASD) is among the most disabling neurodevelopmental disorders (NDDs) in children. It is characterised by impairments in social interaction, limitiation in communication, and restricted and repetitive behaviours [15]. The disorder is highly prevalent, estimated to affect around 1.5% of the population [102].The onset of ASD symptoms occurs during the first three years of life and the diagnosis can be reliably made as early as 24 months of life [75, 152]. Howether, ASD is usually diagnosed between 38 to 120 months [41, 146, 153]. Yet, an early diagnosis is necessary to ensure an early intervention that takes advantage of higher neuroplasticity [43, 115].

Males are affected 4.2 times more often than females [59]. Causes are not completely understood and include both genetic factors, like the chromosome 15-q11-q15 duplication, and environmental factors such as foetal valproate exposures [170]. ASD is a lifetime disorder and its burden continues in adulthood: only a minority of affected individuals achieve reasonable outcomes. Many individuals remain highly dependent on others for support [83]. ASD is often associated with other NDDs, such as attention-deficit/hyperactivity disorder, tic disorders, developmental coordination disorder (DCD) and comorbidities (e.g., anxiety disorder, epilepsy) [114]. Thus, the heterogeneity is large.

Repetitive behaviours are the only motor symptomatology of ASD included in the current diagnostic criteria of the *Diagnostic and Statistical Manual of Mental Disorders*, fifth edition (DSM-5) [15] and in the *International Classification of Diseases*, 11$^{\text{th}}$ edition [130].

However, movement abnormalities have been discussed since the first clinical descriptions of autism made by Kanner [91] and Asperger [13] who described patients with 'sluggish' reflexes or a 'clumsy' gait. Meta-analyses have confirmed that alterations in motor performances exist [49, 60] in 85% to 90% of cases [120, 99]. Motor difficulties are significantly correlated with social, communicative and behavioural impairments that define the disorder [51]. Cook et al., [37], argued that movement differences, between typical children and those with ASD, may contribute to difficulties in reciprocal social cognition.

Symptoms of developmental coordination disorder (DCD) can be found in ASD [60]. DCD is a disorder characterised by motor delay and dysfunction. How ASD and DCD interact with one another is still controversial. On the subject of motor dysfunction, the DSM-5 now recommends diagnosing ASD and DCD as comorbidities [15]. Some authors support the existence of different disorders that could be caused by the same mechanisms [72,120]. Others consider the motor dysfunctions found in DCD and ASD to be different in nature from one another [137,191]. In a systematic review, Cacola et al. [26] showed that, while DCD and ASD share some behavioural symptoms, distinctions exist in terms of gestural performance, severity of motor challenges, and grip selection. Finally, motor disturbances appear to be among the first manifestations of developmental abnormalities in ASD and could serve as markers of the condition in the first years of life before other core symptoms (i.e., social communication, restricted interests) are visible [75,131].

The clinical assessment of motor coordination in ASD is based on semi-quantitative standardised instruments such as the Movement Assessment Battery for Children (MABC-2) [81]; the NP-MOT (Neuro-Psychomotrian evaluation of the child) [178]; the Test of Gross Motor Development (TGMD-2) [162]; the Bruininks-Oseretsky Test of Motor Proficiency (BOT-2) [33]; or more specifically the Concise Evaluation Scale for Children's Handwriting (BHK) [34], to assess writing skills.

Parental questionnaires are also available, including the DCDDaily-Q [110, 179] and the Dunn questionnaire [50]. For a review about tests to assess DCD, see Albaret et al. [7]. However, it is difficult to recommend a set of standardised and fixed assessments since the autism spectrum is large [114,190] and heterogeneous in terms of a child's commitment to an examination and their intensity of motor dysfunction. Therefore, assessments often require a subjective input from trained professionals, are time-consuming and can be tedious to rate. The evaluation sessions typically group several assessments in a row. To complete this evaluation can be tiring for the children. In addition, such assessments do not allow ecological (in situ), day-to-day context evaluations. Therefore, these tests have a low access and waiting lists of six or more months are frequent, even in richest countries [79].

Computational technologies offer the opportunity to overcome these obstacles, enabling new ways for characterizing children's behaviour in more natural contexts. This challenge has been faced by Neuro-Developmental Engineering (NDE) with the goal of providing "new methods and tools for: (1) understanding neuro-biological mechanisms of human brain development; (2) [performing] quantitative analysis and modeling of human behavior during neurodevelopment; [and] (3) assessing neuro-developmental milestones achieved by humans from birth onwards" [30,31]. Applications are numerous and include robotics [156,93,23,90], computer games [73], diagnosis [17,79,93] and behaviour imaging [171,9,10]. Machine learning techniques, and the most recent techniques like deep learning [193,107] in particular, are more and more used in medicine

[176, 107], for instance to analyse brain imaging data in neurological and psychiatric disorders [128]. Recent reviews and articles showed the use of such tools in child and adolescent psychiatry: in the detection of motor anomalies in Attention Deficit and Hyperactivity Disorder (ADHD) [124]; in the assessment of social behaviors in ASD with contact-less and irritation-free sensors [96]; in the analysis of data from questionnaires and interviews [158]. These tools open new, fascinating approaches as described in [150], where photos taken by children are studied, revealing the world of autism from a first-person perspective. Machine learning was also used in neurological disorders, [119] such as in dementia [85] or Parkinson, [55] as a characterization tool, but also for the development of new treatments, such as the ones based on brain-computer interfaces [108]. Yet, a review focusing on the assessment of motor difficulties in children with autism is still missing.

Here, we present a systematic review of the automatic assessment of movement disorders in children with ASD using new technologies. After briefly describing the different motor impairments found in ASD, we review NDE attempts to automatize motor dysfunction assessments. Given the variety of motor domains, we propose to distinguish the areas of (1) equilibrium; (2) motor coordination; and (3) motor synchrony and movements during social interaction.

2 Method

We systematically searched the Institute of Electrical and Electronics Engineers (IEEE) [1], Medline [142] and Scopus [2] databases from inception to October 2018 with the following items: *'autism' AND 'movement' AND ('automatic' OR 'computational' OR 'engineering')*. The search was limited to articles written in English. We screened all the identified reports, studies and reviews by reading the titles and abstracts.

2.1 Inclusion and exclusion procedure

Eligible studies included those that discussed the following topics: (1) automatic assessment/new technologies, (2) motor behaviours, and (3) children with ASD. We excluded studies that involved direct cognitive function assessment, patient- or parent-reported outcomes such as online questionnaires. We excluded studies with computational models of movement like Idei et al, 2017 [84]. We also excluded eye-tracking studies (see Papagiannopoulou [134] for a systematic review), emotion expression studies focusing in facial action units in laboratory settings (see El Kaliouby et al [54] for a review), driving assessment studies (see Wilson et al. [188] for a review) and sleep assessments studies (see Moore et al [122] for a review) since these points were tackled by reviews cited above. We excluded studies that did not include children since the variability with studies putting also adults would increase too much the variability.

2.2 Data selection

From the relevant articles, we extracted the following information: type of movement evaluated; level of evidence, according to the "Rational Clinical Examination Levels of Evidence" table [160]; study design, in terms of the number of subjects included and the existence of a control group; automatic system used to identify ASD peculiarities e.g., camera, tablets); sampling frequency; type of setting (i.e., experimental laboratory vs. ecological setting); socio-demographics of the participants (age and sex); clinical assessment; statistical/machine learning method used to explore the data; and the main results of the study. When sub groups of children with ASD were identified (autism, Asperger's syndrome and pervasive developmental disorder-not otherwise specified), the sample size was pooled in the generic term ASD according to the DSM-5 [15]. The report was complied according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [121].

3 Results

In total, we identified 54 relevant articles dealing with new technologies, motor behaviours and including children with ASD. Figure 1 details the process and output for studies selection and inclusion. The included studies were quite heterogeneous as most movements can be impaired in ASD including equilibrium (such as posture, gait), motor coordination, and motor synchrony and movements in interaction. Also, they used several devices to capture relevant motor information such as cameras, 3D cameras, motion capture systems, accelerometers within watches or smartphones. Interestingly, since 2012, the number of studies increased dramatically as technologies have become less invasive, more precise and more affordable (Figure 2). In the following sections, we summarize the main results of the present review. We opted to briefly detail each ASD motor domain even when no NDE study was found in said domain to indicate further areas of research that may be appropriate to explore.

3.1 Equilibrium (N = 24)

3.1.1 Tonus

Hypotonia and ligamentous hyperlaxity are often described in children with ASD [76, 118, 159]. In a population-based study [157] as well as a retrospective analysis of parents' early concern [75], a low muscle tone in infancy predicted autistic traits or ASD. Children with ASD presenting a disharmonious tonic typology may be encountered with a hypertonia of trunk muscles and the of proximal muscles of the lower limbs, and a hyperlaxity of the ankles and of the proximal and distal muscles of the upper limbs (wrists and shoulders) [136].

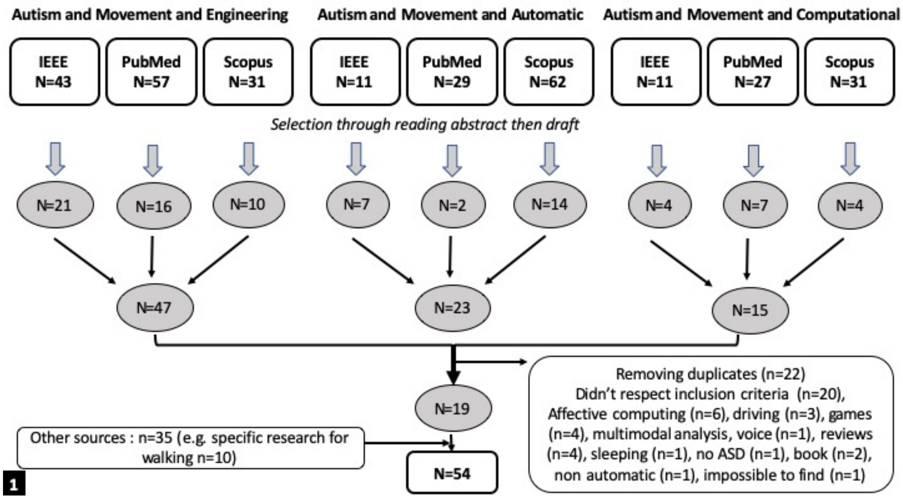

Fig. 1: Flowchart of study inclusion

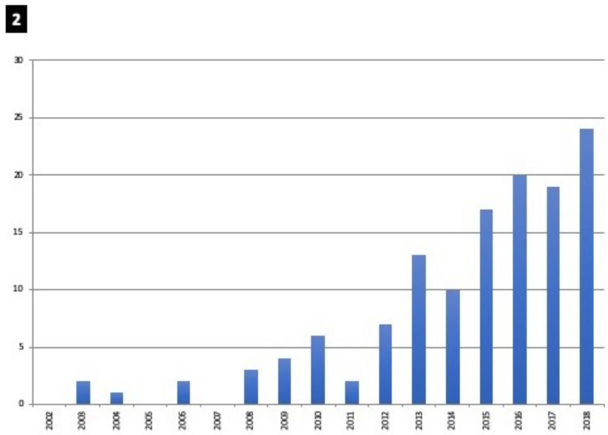

Fig. 2: Number of publications found in PubMed (Medline) according to the search terms 'autism' AND 'movement' AND ('automatic' OR 'computational' OR 'engineering') »

However, we did not find any distinct method used to automatically assess the tonus.

3.1.2 Posture analysis (N = 10, Table 1)

Posture instability is common in children with ASD (for reviews see [98,166]), with an increase in the size of the support polygon and shorter strides [127] that can lead to difficulties like holding up one own head, sitting and walking [87].

Assessment with consumer devices

Travers et al. [175] evaluated the balance and postural stability with a Nintendo Wii™ (Nintendo, Kyoto, Japan) balance board (Figure 3A), a device developed for video games, that had sensors in its four corners and a quite high sampling frequency (60 Hz). Twenty-six individuals with ASD and 26 age-and-IQ-matched individuals with typical development stood on one leg or two legs with eyes opened or closed on a Wii balanceboard. They observed a significant intergroup difference in postural stability during one-legged standing, but no difference between the groups during two-legged standing.

Fig. 3: Sensors used to assess posture in ASD:
Nintendo Wii balance board™ (A); Kinect™ (RGB-D sensor) (B).

Stereotypical behaviours during resting state

Inertial measurement units are sensors that can include a gyroscope (to measure rotation), an accelerometer (to measure acceleration), and a magnetometer (to measure direction, strength, or relative change of a magnetic field). Some are can be used to measure motor stereotypies.

Albinali, Min and Goodwin proposed to use wireless three-axis accelerometers and pattern recognition algorithms to automatically detect body rocking and hand-flapping in six children with ASD [8,117,70,69]. In average, pattern recognition algorithms correctly identified approximately 90% of stereotypical motor movements repeatedly observed in both laboratory and classroom settings. These devices were worn by children in ecological environments like classrooms.

Rad et al. [143,144,145] used wireless inertial sensing technology to detect stereotypical motor movements in children with ASD. A Deep learning algorithm allowed for these investigators to outperform the traditional classification scheme on the handcrafted features but the interpretability remains difficult since the features automatically extracted are difficult to understand.

RGB-D sensors (RGB-D for "red, green, blue - depth") extend common cameras with depth information. The Kinect™ (Microsoft Corp., Redmond, WA, USA), in particular, is a RGB-D camera developed to pair with video games, to assess user positioning with depth analysis. The Kinect™ v1 uses structured light and projects bi-dimensional patterns to estimate the dense depth information of the scene: reflections of such patterns allow the computation of three-dimensional information of the objects in the environment. The Kinect™ v2 uses in addition time of flight of the signal between the camera and the object, making it less sensitive to the illumination conditions than the Kinect™ v1. Goncalves [68,67] employed both accelerometers in a watch and a Kinect™ system (Figure 3B) to measure stereotypic hand-flapping movements in children with ASD. A dynamic time warping algorithm was used to classify the data from the Kinect™ system. The accelerometers appeared to be more accurate than the Kinect™, which present the advantage not to require the child to wear any device or marker.

Resting state during magnetic resonance imaging

From resting-state functional magnetic resonance imaging scans performed on 304 children with ASD and 304 control group children, Torres et al. examined the noise-to-signal ratio of micro-movements present in time-series of extracted head motions [172]. After complex pretreatment and data analysis, the authors hypothesized the existence of micro-movements as potential biomarkers of ASD.

3.1.3 Gait (N = 14, Table 2)

Walking pattern appears to be altered in people with ASD [182,183]. Several abnormalities have been described in ASD including toe-walking [184], variable stride length and duration, incoordination, head and trunk positionning abnormalities during walking, reduced plantar flexion, and increased dorsiflexion [27] (for an in depth review, see Kindregan et al. [94]). During our research, we found 14 studies investigating automatically gait difficulties in ASD (Table 2)

Gait analysis with infrared cameras

The field of NDE has proposed several attempts to assess and quantify gait-related ASD characteristics. Nobile et al. [127] set up a system composed of eight infrared cameras (Elite System™, Bts ® Bioengineering, Milan, Italy). The use of several cameras allowed the authors to follow each part of the body at any time (limits the occlusion). They explored gait on a 10 m walkway in children with ASD (N=16) and controls (N=16) who were equipped with markers. Children with ASD showed a significantly shorter stride length and wider step width and a marginally slower mean velocity. The range of motion in the hips and knees was also significantly reduced. Using an automatic motion analyser (Vicon Motion Systems, Oxford, UK) made of markers and six cameras, Longuet et al. [100] showed that the steps of children with ASD (N=11) were generally smaller and slower than those of controls (N=9). Movements of the head, shoulders and hips were more variable in children with ASD. Using the same setup, Eggleston et al. [53] found that children with ASD (N=10) exhibited unique lower-extremity joint asymmetries. Further, Calhoun et al. [27] reported significant differences between children with ASD (N=12) and controls (N=22) regarding cadence, and kinematics of peak hip and ankle. However, Chester and Calhoun [35] did not find any differences in asymmetry during walking between the two groups studied.

Attempts to automatize the diagnosis

Noris et al. [129] measured a collection of three-dimensional coordinates from 14 markers applied to the joints of the lower-body area of 22 children (11 children with ASD, 11 controls) using an infrared camera (motion-capture). Using an echo state network (a form of recurrent neural networks – NN) they were able to extract differences in the cycles evolution and could stratify children with ASD and controls with an accuracy of up to 91%.

Ilias et al. [86] used a NN and a support vector machine (SVM) to classify temporal, spatial, kinetic and kinematic gait parameters of 32 controls subjects and 12 children with ASD. They acheived an accuracy of 95%, a sensitivity of 100% and a specificity of 85% for the SVM. Hasan et al. [77] performed a stepwise discriminant analysis to select features and then established three layers of an artificial NN to classify gait with an accuracy of 91.7%, a sensitivity of 93.3% and a specificity of 90.0%. Torres [173] used a motion capture system (Polhemus Liberty™, 240 Hz continuous gamma family of probability distribution, ; Polhemus, Colchester, VT, USA) to check for differences between children with and without ASD and with Phelan McDermid syndrome, a rare genetic syndrome that has a high penetrance of ASD.

Pressure systems

Rinehart et al. [148] asked 11 children with ASD and 11 controls to walk on a GAITRite Walkway (CIR Systems Inc., Franklin, NJ, USA) and observed that a greater difficulty was experienced by children with ASD regarding walking along a straight line and dealing with the coexistence of variable stride length and duration. Children with ASD were also less coordinated and rated as more variable and inconsistent (i.e., they showed reduced smoothness) compared to the control group. Postural abnormalities were noted in the head and trunk of the ASD group.

Rinehart et al. used the Clinical Stride Analyser (B & L Engineering, CA, USA) (Figure 4), a pressure system, to evaluate children's walking [147]. The group with ASD (N=10) showed a significant increase in stride-length variability in their gait in comparison with the control group (N=10) and Asperger's disorder (N=10) participants. No quantitative gait deficits were found for the Asperger's disorder group.

Hasan et al. [78] used two force plates embedded in the middle of a walkway to measure the ground reaction force during gait. Children with ASD (N=15) had a different ground reaction force than the control group individuals (N=25), especially throughout the first half of the stance phase. Specifically, they showed a higher maximum braking force, lower relative time to maximum

Fig. 4: The clinical stride analyser

braking force, and lower relative time to zero force during mid-stance. Children with ASD were also found to have a reduced second peak of vertical ground reaction force in the terminal stance.

Pre/post therapy study

Steiner [163,164] used a gait analyser constructed with four cameras and Ariel Performance Analysis System™ (Ariel Dynamics, Trabuco Canyon, CA, USA), to compare the effects of riding therapy on children with ASD (N=26). Half of study participants performed the riding therapy with horses, while the other half composed the control group. Of note, the length of the gait cycle became more stable in the sagittal plane after the riding therapy.

Overall, these gait study set-ups were quite precise, achieving classification models with high accuracies. However, using those techniques for clinical evaluation seems difficult and costly: such studies required trained teams, the activities recorded were highly specific and the generated models seemed difficult to be generalized to ecological scenarios.

3.2 Fine motor skills requiring hand dexterity and visuomotor coordination (N = 12, Table 3)

Young children with ASD have poorer fine motor skills in tasks like object handling, grasping and visual-motor tasks [88,141]. It seems there is an higher rate of left-handed people in the ASD population but the methods of evaluation used are heterogeneous and the results are inconclusive [140,135]. Children with ASD also display differences in movement planning and execution [109].

3.2.1 Grasping (N = 9)

Sacrey et al. [151] showed in a review that grasping in ASD is impaired. Researchers tried to characterize this impairment using different kind of technical aids, as infrared cameras, accelerometers, gyroscopes and more complex robotics systems.

Infrared cameras

Crippa [40] revealed that simple upper-limb movement could be assessed by a three-dimensional infrared camera optoelectronic 60-Hz SMART-D system™ (Behavior Tracking System Bioingegneria, Garbagnate Milanese, Italy), with picked up markers placed on the wrists and hands of participants. This system was useful to classify the movements of low-functioning children with ASD using an SVM classifier, based on seven features related to the goal-oriented part of the movement. The system obtained an accuracy of 96.7 %. Campione [29] used the same system showing that children with ASD (N=9) took a longer time to complete the whole reaching movement. However, kinematics of the grasp component were spared in ASD, while early kinematics of the reach component were atypical. During a grasp and throw task with a ball, Perego et al. [139] asked children with ASD (N=10) and controls (N=10) to wear markers on the shoulders, elbows and wrists. The same SMART™ system was used. Using an SVM algorithm to discriminate the diagnostic of children by the means of upper-limb kinematics, during reaching and throwing, these authors revealed a difference in the number of movement they performed overall, the total duration of their movements and their wrist angle whilst reaching. The SVM algorithm proved to be able to separate the two groups: an accuracy of 100% was achieved with a soft margin algorithm, while an accuracy of 92.5% was achieved with a more conservative one. Cook et al. [38] recorded trajectory, velocity, acceleration and jerk, while adult participants with ASD (N=14) and a matched control group, conducted horizontal sinusoidal arm movements. They also performed a motion perception task. They classified observed movements as 'natural' or 'unnatural'. Individuals with ASD moved with atypical kinematics; they did not minimize jerking to the same extent as the matched controls, and moved with greater acceleration and velocity.

These methods are more invasive than RGB-D sensors and can be used only for very specific tasks taking just few minutes. Indeed, the markers that children need to wear can restrict their movements and cannot be used in ecological settings.

Accelerometers, gyroscopes and robotics system

Several studies have examined grasping from sensors (inertial measurement units) included directly within the targeted object. Campolo et al. developed a ball with sensors to characterize the grasping of children with ASD [31]. David et al. compared children with ASD (N=13) to control peers (N=13) and found prolonged latency between grip and load forces, an elevated grip force at the onset of load force, and increased movement variability, which can be taken as signs of temporal dyscoordination in ASD [42].

Wedyan and Al-Jumaily [185, 186] used wearable sensors and sensor insides shapes to measure movements during three upper-limb tasks, including: (1) throwing a small ball into a transparent plastic then inserting the ball into a tube; (2) placing a block into a large open box, then making a tower with four blocks; and (3) inserting a shape into a small slot. Both studies extracted features of interest automatically, using linear discriminant analysis. The first task was deemed as the best to classify a high risk versus low risk of autism with an accuracy of 81.67% using a NN (an extreme learning machine).

Marko et al. [111] analyzed the reaching movements of children with (N=20) or without (N=20) ASD while holding the handle of a robotic manipulandum. In random trials, the reach action was perturbed, leading to errors that were perceived either through vision or proprioception. Children with ASD outperformed control children when learning from errors that were perceived through proprioception, but underperformed control children when learning from errors that were perceived through vision.

3.2.2 Pointing

Torres et al. [171] used a different motion capture system (Polhemus Liberty™, 240 Hz; Polhemus, Colchester, VT, USA) and the MouseTracker software (Freeman and Ambady, 2010 ; Medford, MA 02155, USA). The participants performed two pointing tasks; one with and one without a decision-making task on a touch screen. The authors defended that ASD could be characterised by micro-movements and argued that they correspond to the re-afferent feedback signal, giving rise to precise stochastic signatures of movement fluctuations over time.

3.2.3 Touching and drawing (N = 2)

Anzulewicz et al. [11] used tablets with touch-sensitive screens and embedded inertial movement sensors (iPad Mini™; Apple, Cupertino, CA, USA). They asked children with ASD (N=37) and controls (N=45) to play two serious games (a video game developed for educative and diagnostic purpose, i.e., cutting fruits and sharing them and then drawing and colouring a chosen shape). Different decision forests models of the children's motor patterns were employed to classify ASD against controls The most effective algorithm achieved an accuracy of 93%. The children with ASD displayed greater force at impact and a different pattern of force output onto the device during gestures. Fleury et al. used an electronic tablet (Wacom™ Co., Ltd., Kazo, Japan) to record the drawing of circles under different conditions (with dominant and non-dominant hands and, for each, in continuous, discontinuous and continuously as fast as possible actions) of 23 children with ASD and 20 controls. Children with ASD showed an intact ability to consistently produce continuous movements, but an increased degree of variability in the production of discontinuous movements [58].

3.2.4 Writing (N = 1)

Writing evaluation has shown that patients with ASD have lower handwriting scores. In addition, the handwriting quality of ASD participants is impaired with bigger size of letters and lower measures of legibility (for a review see Finnegan [56] and Verma [181]). We failed to find in the literature any automatic assessment of writing in children with ASD although recent research is available on the subject for control children [14,62]. However, Sparaci [161] showed that a virtual pursuit rotor exercice [4] with a pen on a tablet was harder for patients with ASD than for controls to perform.

3.3 Movement used in social interactions (N = 12, Table 4)

Monitoring movements involved in social interaction is important because these difficulties are the best described and are required for ASD diagnosis. Affective computing [54] has shown that it is possible to measure the synchrony of motion history with performing metrics that are now openly available such as Python SyncPy library [180].

3.3.1 Motor coordination or synchrony (N = 4)

Fitzpatrick et al. [57] used sensors attached to the end of two pendulums manipulated by a teenager and by her/his parent to record angular displacements. Such displacements were tracked with a magnetic motion tracking system (Polhemus Liberty™, Polhemus, Colchester, VT, USA) and a 6-D Research System software (Skill Technologies, Inc., Phoenix, AZ, USA). In particular, they compared the displacements from teenagers with (N=9) or without ASD (N=9) showing that adolescents with ASD synchronised less spontaneously or intentionally.

Fulceri et al. [61] found similar results during an interpersonal motor coordination task. Both static and dynamic movements were measured through a wearable embedded system that integrated information from a tri-axial gyroscope and a tri-axial magnetometer and accelerometer.

Marsh et al. used rocking chairs with a Polhemus Fastrak magnetic tracking system™ (Polhemus, Colchester, VT, USA) to assess interpersonal synchrony between children and their parents. These authors showed that children with ASD (N=8), opposed to controls (N=15) experienced a disruption of spontaneous synchronisation [112].

Cameras or cameras with a depth sensor (RGB-D camera) have been used to evaluate motor turn-taking and motor synchrony. Delaherche et al. [47] video-recorded cooperative-joint action tasks and automatically extracted features that characterised interactive behaviours such as auditive turn-taking or synchronised gestures. Features characterizing the gestural rhythms of the researchers and the duration of their gestural pauses were particularly accurate for discriminating their interactions with patients with ASD (N=7) and controls (N=14).

3.3.2 Interpersonal distance

In general, interpersonal distance is larger among children with ASD [149, 32, 65, 177]. However, sometimes, children with ASD can position themselves very close to other people, violating others' personal space [92]. We failed to find, in literature, automatic assessments of interpersonal distance in children with

ASD. This kind of evaluation would come as soon as multiple-people-tracking technology [5], such as the open access libraries OpenPtrack [3], will allow a continuous and efficient tracking of children in a room. Specifically, by employing several cameras, such systems will automatically assess the interpersonal distances between children, evaluating if any child is isolated and stay far from the others or not.

3.3.3 Motor imitation (N = 4)

Social deficits in ASD have been linked to imitations difficulties [149]. Motor imitation has been investigated by NDE in several protocols. Xavier et al. [191] used an imitation task with a virtual tightrope walker standing and moving. They compared children with ASD (N=29), children with developmental coordination disorder (DCD; N=17) and controls (N=39). They showed that (1) interpersonal synchronisation (as evidenced by the synchrony between the participant's and the tightrope walker's bars) and (2) motor coordination (as evidenced by the synchrony between the participant's bar and its own head axis) increased with age and were more impaired in children with ASD. Motor control was more impaired in the ASD group than in the DCD and control groups.

Boucenna et al. [22] and Guedjou et al. [74] developed a robotic interactive system, based on a camera, in which a child imitates the robot's motor postures and then the robot imitates the child's motor postures. The system was able to extract a motor signature indicating when the robot was interacting with children with ASD (N = 15) as compared to control children (N = 15) or adults (N=11). The system required more computational power, i.e., more neurons in the neuron networks to achieve posture recognition in individuals with ASD than in control children. [74].

Bugnariu et al. [24], showed that children with ASD (N=4) had poorer performance while imitating a robot than control children (N=4). Authors collected the children's movements through a motion-capture system with markers and exploited them using dynamic time-warping. This algorithm is interesting due to its ability of matching the temporally inexact nature of imitation.

3.3.4 Joint attention (N = 2)

Impairment in joint attention (JA) is a key symptom of ASD that appears early in development [45]. Most researchers have used eye trackers (a video camera with an infrared light source following the subject's gaze) to show that initiating and responding to joint action from someone else are positively correlated with social orienting [89]. However, as gaze usually anticipates head movements during natural interaction, an estimation of JA can also be achieved focusing to the head pose, exploiting RGB or RGB-D data.

Using this method, Anzalone et al. showed that JA was impaired in children with ASD [9], proposing new metrics able to describe it through head pose and posture [10].

3.3.5 Orientation to social signals and name calling (N= 2)

Martin et al. used a computer vision-based head-tracking software (Zface [6]) while exposing children to different social and non-social stimuli [113]. Children with ASD exhibited larger yaw displacement, indicating pronounced head-turning, and a higher head yaw and roll speed, indicating faster head-turning and face inclination. These dynamics were specific to the social stimuli condition. However, they did not find a difference in vertical movement (pitch). Aside from the specific study, this approach could be also useful to diagnose head stereotypies such as repetitive head-banging.

Campbell et al. used a tablet to display videos to 22 children with ASD and 82 controls (1.5-2.6 y.o.). Only 8% of toddlers with ASD oriented to name-calling on more than one trial as compared with 63% of toddlers in the control group (p=0.002). Orienting latency was in average significantly longer for toddlers with ASD (2.02 vs 1.06 seconds, p=0.04) [28].

3.4 Ecological assessment (N = 6, Table 5)

Although this field is still limited, we found 6 studies with technologies used in an ecological context (Table 5). We believe that the ability to automatically measure behaviours in an ecological context would offer great opportunities in the future.

3.4.1 Accelerometers (N = 2)

Accelerometers were first used in the assessment of sleep among children with ASD [187]. By putting a GT3X device (Actigraph, Pensacola, FL, USA) on the right hip for seven consecutive days, Memari et al. [116] showed a reduction in physical activity in ASD participants during adolescence. However, Pan and Frey and Bandini [133,16] did not observe any difference in physical activity.

3.4.2 Videos collected at home (N=4)

Home movies have been used for years to investigate early infant development before a diagnosis of ASD is made. Some authors have found that this approach can improve diagnosis [169], while others did not replicate this result [131]. Many analysis have been conducted by manually annotating videos [132,12]. In infants with ASD, researchers have observed a reduced response to their name, a reduced looking towards others, a lower quality and quantity of eye contact, a decrease of positive facial expressions and of inter-subjective behaviours for instance during a joint attention task (for a review see Saint Georges et al.

[152] and Costanzo et al. [39]). Infant motor symmetry and gait were explored by Maestro et al. [104,105,103]. Infants who went on later to develop autism showed more asymmetry and gait dysfunction than control children. Using the same Pisa home movie database, Cohen et al. [36] and Saint-Georges et al. [154] employed a computational analyses of synchrony and a motherese classifier [106] to refine assessments of early interaction. They showed specific patterns of early caregiver-infant interaction, in those who go on to develop ASD.

Recently, Egger et al. [52] developed a smartphone application to reach 1756 families who uploaded 4441 videos recorded in their child's natural settings. Using the software IntraFace to automatically annotate face behaviours, they identified significant differences in emotion and attention according to age, sex, and ASD risk status. The face direction and emotion expression can also be assessed with the software OpenFace. This strategy was for instance used by Higuchi et al. [82], who showed how a computer interface helped observers in performing video coding of social attention, and how human judgment compensates technical limitations of the automatic gaze analysis.

4 Discussion

4.1 Main findings

This review shows that many motor activities can be tracked automatically in ASD with a good level of sensitivity. Exploiting such automatic classification techniques, authors found differences between children with ASD and controls in all the domains of movements, obtaining sometimes high levels of accuracy. In other studies, the proposed techniques allowed the detection of stereotypical motor movements.

This 'neurodevelopmental engineering' field [30,31] is a rapidly evolving area of research that could provide more objective evaluations, especially during screening, but also an improved understanding and monitoring of the development of children with ASD or other neurodevelopmental disorders [44, 155].

In the presented cases, the devices that were employed to measure movements showed different advantages in terms of sampling frequency and spatial precision, or adaptation to behavior subtypes and costs (Figure 5) [25]. Some of these devices allow the capture of large amounts of ecological data, while being cheap, and available in the consumer market. With time, they will became less invasive, more affordable and more available for ecological contexts.

The number of studies collecting data in natural environments has been usually modest, due to the challenges faced in their completion. However, thanks to new technologies, such studies become more and more feasible. Assessment using tablets (writing, touching, pointing), for instance, is an emerging field that employs data collected at home from young children aged from three to six years old. From three years old, the literature analysed shown how posture and stereotypies can be evaluated with cheap sensors like accelerometers or devices developed initially for video games (Kinect and Wii balance board). Such sensors are very useful for ecological contexts. At the same time, some studies have been realised in semi-structured environments as classrooms: these locations are interesting as more easily approachable than the home or other unstructured scenarios, because of the partial control of the environment they offer, together with the possibility of collecting structured data.

Within the presented technologies, more and more motor activities are being investigated: posture, walking, grasping... Even when we consider social difficulties in ASD, we can measure the behaviours involved in social interactions, including head pose, synchrony or interpersonal distance. Other motor activities like writing could be targeted thanks to the development of hardware and analysis methods implemented in tablets [14]). Gait has been evaluated in a larger number of studies (N= 14). However, children needed to be older to do the proposed assessment (from five years old). We think that this strategy is limited for ASD screening since other evaluations are easier to do in ecological settings at an earlier stage.

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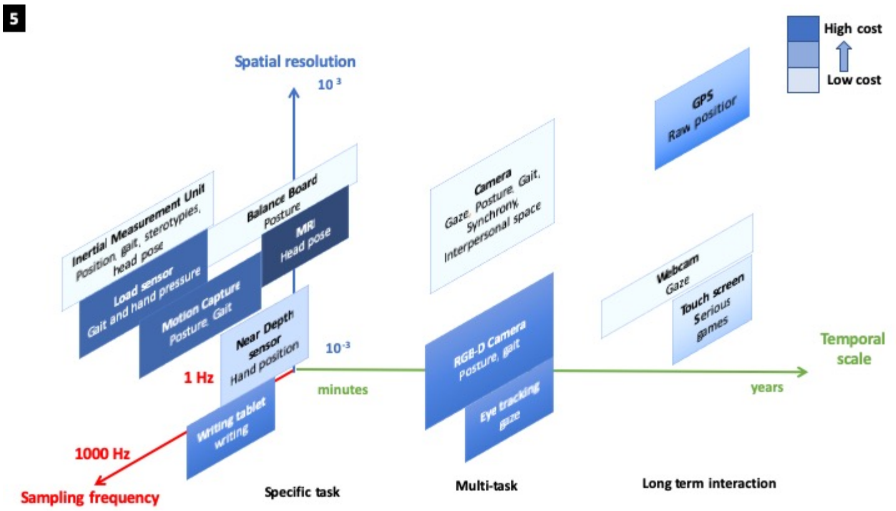

Fig. 5: Properties of motion sensors in terms of sampling frequency, spatial resolution and temporal scales of use

The different computational methods employed in the explored studies highlighted also a trade-off between interpretability and accuracy (Figure 6). In particular, different strategies of data analysis have been applied to extract automatically movement disorders in ASD. Some teams have developed sets of features able to model the movements, improving the interpretability of the obtained models. Other teams applied advanced machine learning approaches, like deep learning, directly to raw data. While the latter can be more accurate, the interpretability of the outcome is more complicated. Indeed, explainability and interpretaibility are important and difficult goal beyond the objective of accuracy [19, 18]. Some data analysis strategies permit real-time feedbacks whereas others have higher computational cost and such feedbacks are not feasable. Some of these algorithms have made it possible the use of less-invasive and more accessible devices, as the tracking technologies that do not use body markers, (a simple camera could be sufficient): OpenFace [52] instead of an eye-tracker or OpenPose (Figure 7A) instead of a motion capture system.

6

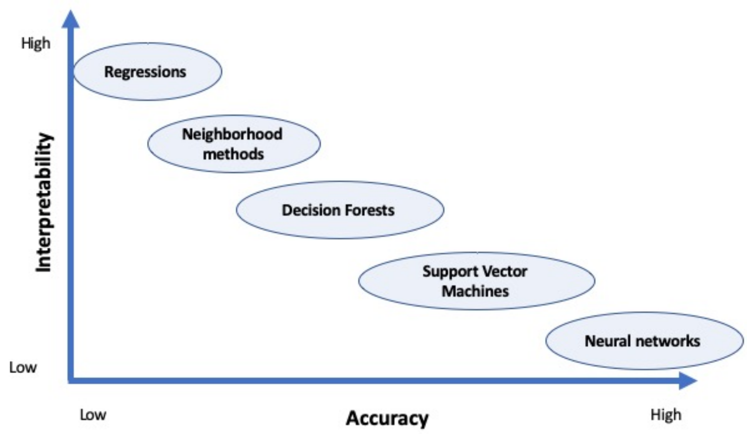

Fig. 6: Properties of main machine learning methods in terms of interpretability and accuracy

4.2 Limitations

The quality of evidence obtained in the explored studies does not reach the clinical standards for routine diagnostic assessment. Most of the studies do not report how and if they limited the risk of some biases. Blinding of the diagnosis when validating a system and pre-registration of the protocol could limit such biases. Often, the clinical data are not precised and even the gold standard clinical assessements (i.e., Autism Diagnostic Interview-Revised –ADI– or Autism Diagnostic Observation Schedule –ADOS®-2) are not performed [101]. The highest medical standards would require the recruitment of large series of consecutive patients [167]. An open science framework with accessible data and software would enable easier replications in different populations to increase the generalisation of the results [123].

There is a lack of cognitive models to bridge the gap between cognitive sciences and NDE. From a theoretical point of view, future research should be combined with computational approaches of ASD [71,168]. Some authors (eg. [174]) in particular, believe that integrating a perception-action perspective would be fruitful since movement production in ASD has been linked to a movement-perception deficit, which looks to be a prerequisite for the understanding of intentions of others, posture, and facial expressions and thus social abilities and communication. Thesee sensorimotor competencies could be the primum movens of an atypical developmental cascade that should be further validated [21,64].

Large datasets would require a centralised collection of data that would ensure easier characterisation and clustering. However, medical data are sensitive and their use is associated with security and confidentiality issues. For example, home movies or data from smartphones [52] need secured internet transfer and storage on distant powerful computer for data analysis. From another perspective, the development of open science suggests the need of sharing data and algorithms to improve transparency and reproducibility. Beyond privacy issues and open-source strategies, data and algorithms would require appropriate business models for private companies investigating in the field.

Our systematic review was completed on October 2018 even if more recent we can't pretend to be systematic after this date. Due to (1) increase of publications in this field (Figure 1), (2) the diversity of motion sensors, (Figure 3) and analysis methods (Figure 4), new systematic reviews will be necessary in the future with more recent papers. More specific scopes could be useful (1) the younger children, since the expected therapeutic outcomes would be larger with early rehabilitation, (2) the motion sensors that would be the less invasive (best tolerance for the children), and the most easily scalable to a wide audience, (3) the data analysis method that would be the most accurate, (4) the data analysis methods and user interface that would enable the best interpretability and trust among end-user.

4.3 Perspectives

We think that movement computing [125] of automatically measured movement would be useful to help the assessment and monitoring of individuals with ASD. Similar terms are coined regarding other areas of automatic assessment: social computing, affective computing, and vision computing.

A new theoretical framework known as *ethomics* seeks to assess behaviour extensively, in a reproducible way, as it is now done in genetics (genomics), brain connections (*connectomics*) or proteins (*proteomics*) [66]. We think that these technologies will achieve this goal. Behavioural assessment could help in identifying more homogenous endophenotypes.

Several teams [192,171,11] have suggested that these assessment methods will allow researchers to define a motor signature of ASD. In this context, the proprioceptive feedback that allows online guidance of movement may be disrupted, creating resonance and control errors [171]. If this motor signature is specific, we would not expect to find it in children with DCD, intellectual disabilities or attention-deficit/hyperactivity disorder, while it would be often associated with ASD. It would be necessary to disentangle different kinds of movements such as (1) goal directed movements (as pointing to a target under request), (2) automatic movement such as motor mirroring, (3) cultural movements as writing that could involve different cerebral computations and thus lead to different difficulties.

Open access and annotated benchmark datasets in the field would be helpful to test several classification methods, select the best and improve reproducibility like it did yet in other domains [107]. ABIDE dataset allowed to analyse functional brain peculiarities using MRI data[80,48,126]. However, from this dataset, Zhang et al concluded that the neuroanatomy of ASD does not exist, but is highly age and gender dependent [194].

In a recent systematic review assessing computer vision in ASD, Belen et al. concluded that "until recently autism datasets have been relatively small when compared to other datasets in which machine learning has seen tremendous application" [46]. In the ASD detection video dataset, 20 children with ASD and 20 controls performed reach-to-grasp actions. They grasped a bottle and performed different subsequent actions (e.g. placing, pouring, passing to place, and passing to pour) [196].

This review shows that this work would especially be useful for early motor disturbances. The DREAM dataset, collected during Robot Enhanced Therapy, was the only one found in this research field [20]. It has several advantages (1) the dataset is openly accessible and would enable to have the role on a benchmark database on which different analysis teams could perform different classification algorithms, (2) the number of patients is important (n=61), (3) the diagnosis is based on a reference test ADOS, (4) the data was collected longitudinally, (5) the therapy sessions are evidence-based (Applied Behavior Analysis), (6) the motion sensors are not invasive and do not need to be worn by the patients : RGB, RGB-D, sensorized table (25 Hz) [20]. No data analysis was published on this database yet.

These children are highly variable between themselves[114,190]. Due to the important impairment of these children like communication difficulties, and behaviour disturbance, the sample size of the studies is often small. Most of the reported studies are cross-sectional. These technologies could be useful longitudinally to follow (1) the spontaneous evolution of children to understand the developement and (2) efficacy of care to restore a better developmental trajectory. During the therapy these methods could be useful to provide motor feedbacks that can be useful for both patients and therapist, e.g. like was done in dysgraphia for DCD [63].

These new methods for measuring motor difficulties could open new insights in the development of ASD and, in general, of social cognition. The development of sensorimotor abilities occurs before the development of communication and socialisation skills. Sensory difficulties are frequent in children with ASD. [195,97]. Severe sensory issues are associated with more prominent social difficulties and lower adaptive functioning [95]. In the same way, impaired praxis (that includes gestures to command, imitation, and tool-use in children) is strongly correlated with social, communicative, and behavioural impairments that define ASD [51]. Future research would assess whether this fine sensorimotor reaction to social scenes could be an early development step required for the early acquisition of social competences [165,189].

In addition, with the development of easy-to-use devices that can track and monitor the movements easily, several serious games are emerging. For instance Pictogram Room (University of Valencia, Valencia, Spain) allows the tracking of the posture of the child with a Kinect™ (Figure 7B). This posture tracking is displayed on a screen and with an augmented reality system. The game can ask the child, to catch some virtual items or to adopt special postures, to perform rehabilitation. Other systems could allow the development of adapted robotic behaviours for interactions with children with ASD [138].

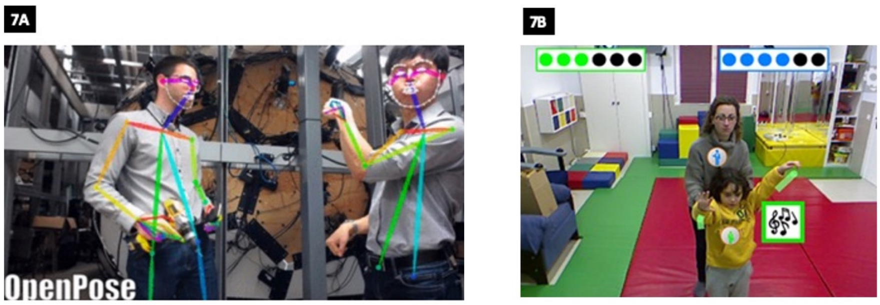

Fig. 7: Screenshots from the use of Open Pose (A) and from the serious game Pictogram Room (B)

5 Conclusion

Movement disorders are found in ASD. However, there is no clear theoretical or clinical framework that could easily explain all of them. The motor assessment of ASD is usually clinical, costly and tedious. New technologies offer the possibility for researchers to measure more objectively the specificities of movement disorders in ASD and eventually could lead to characterizing a specific motor signature or subgroups of individuals with ASD based on motor signature. It is likely necessary to begin to collect standardised large amounts of movement data to better understand the specificities of movement disorders in ASD and to enable descriptions allowing the screening and identification of more objective endophenotypes.

6 Acknowledgements

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7 List of abbreviations

- ASD: Autism spectrum disorder,
- ADI: Autism Diagnostic Interview-Revised,
- ADOS®-2: Autism Diagnostic Observation Schedule -2,
- BHK: Concise Evaluation Scale for Children's Handwriting,
- BOT-2: Bruininks-Oseretsky Test of Motor Proficiency,
- CARS: Childhood Autism Rating Scale,
- CNN: convolutional neural network,
- DBD: Developmental Behaviour Checklist,
- DCD: developmental coordination disorder,
- DCDDaily-Q: developmental coordination disorder daily-questionnaire,
- DSM-5: Diagnostic and Statistical Manual of Mental Disorders, fifth edition,
- GARS: Gilliam Autism Rating Scale,
- Hz: Hertz,
- IEEE: Institute of Electrical and Electronics Engineers,
- ICBS: Infant and Caregiver Behavior Scale,
- ICD-10 : International Classification of Disease,
- JA: joint attention,
- MABC-2: Movement Assessment Battery for Children,
- M-CHAT: Modified Checklist for Autism in Toddlers,
- M-CHAT-R/F: Modified Checklist for Autism in Toddlers, Revised with Follow-Up (M-CHAT- R/F),
- MRI: magnetic resonance imagery,
- MSEL:Mullen Scales of Early Learning,
- NDDs: neurodevelopmental disorders,
- NDE: Neuro-Developmental Engineering,
- NN: neural networks,
- NP-MOT: Neuro-Psychomotrian evaluation of the child,
- PAC: Pedagogical Analysis and Curriculum,
- PDF: Probability Density Functions,
- PEP-R : Profil Psycho- Educatif (PsychoEducational Profile—Revised),
- PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses,
- RBS-R: Stereotyped Behavior Subscale of the Repetitive Behavior Scale-Revised,

– RGB-D sensor: red, green, blue – depth sensor,
– SRS: Social Responsiveness Scale,
– SMM: stereotypical motor movements,
– SVM: support vector machine,
– TD children: typically developing children,
– TGMD-2: Test of Gross Motor Development,
– WASI: Wechsler Abbreviated Scale of Intelligence,
– WISC: Wechsler Intelligence Scale for Children,
– WPPSI: Wechsler Preschool and Primary Scale of Intelligence,

Table 1: **Automatic assessment of posture**

Author name	**Evidence (1: best ; 5: worst)**	**ASD (N)**	**Control (N)**	**Technology used**	**Frequency**	**Setting**	**Sociodemographics of the participants**	**Clinical assessment**	**Statistical/machine learning methods used to analyse the data**	**Main results of the study**
Travers et al., 2013	4	26	26	Wii balance board	60 Hz	Lab	16-30 years (2 females, 24 males in the ASD group and 2 females, 24 males in the control group)	WASI, ADOS or ADI, SRS, RBS-R	ANOVA	Difference in postural stability during one-legged standing but not during two-legged standing
Albinali et al.,2009	4	6	0	Wireless accelerometers, left wrist and right wrist using wristbands, and on the torso	60 Hz	Home and lab	12-20 years (sex not reported)	DSM-IV-TR , RBS-R	Time and frequency domain features computed for each acceleration stream, decision tree (C4.5 classifier in the WEKA toolkit)	In the classroom, an overall recognition accuracy of 88.6% (TP: 0.85; FP: 0.08)
Min et al., 2010	5	4	0	3-axis accelerometer, microcontroller and Bluethooth module for wireless communication with the base station	50Hz	Lab	Not reported	Nor reported	Linear predictive coding (LPC)	Detection of the self-stimulatory patterns with an average of 92.7%.
Goodwin et al., 2011	4	6	0	MITes3-axis wireless accelerometer	60 Hz	lab and class	13-20 years (all males, all ASD)	DSM-IV-TR, RBS-R, CARS	Decision Tree (C4.5 classifier in the WEKA toolkit)	Pattern recognition algorithms identified approximately 90% of SMM repeatedly observed in both settings
Goodwin et al., 2014	4	6	0	Wockets set to transmit three-axis ± 4g motion data	90 Hz	Classroom	12-20 years (all males, all ASD)	DSM-IV-TR, RBS-R, CARS	Decision tree (C4.5 classifier in the WEKA toolkit) and SVM	They observed an average accuracy across all participants over time ranging from 81.2% [true positive rate (TPR): 0.91; false positive rate (FPR): 0.21] to 99.1% (TPR: 0.99; FPR: 0.01)for all combinations of classifiers and feature sets.
Rad et al., 2016	4	6	5	EXLs3 sensor records three-axis accelerometer, gyroscope and magnetometer data	90-100 Hz	Lab and class	13-20 years (all males, all ASD)	DSM-SIV-TR, RBS-R, CARS	Long short-term memory with CNN	Transferring the raw feature space to a dynamic feature space via the proposed architecture enhances the performance of automatic Stereotypical Motor Movements detection system especially for skewed training data.
Rad et al., 2016	4	6	5	EXLs3 sensor records three-axis accelerometer, gyroscope and magnetometer data	90-100 Hz	Lab and class	13-20 years (all males, all ASD)	DSM-IV-TR, RBS-R, CARS	CNN	preliminary evidence that feature learning and transfer learning embedded in deep architectures can provide accurate SMM detectors in longitudinal scenarios.
Rad et al., 2018	4	6	5	EXLs3 sensor records three-axis accelerometer, gyroscope and magnetometer data	90-100 Hz	Lab and class	13-20 years (all males, all ASD)	DSM-IV-TR, RBS-R, CARS	CNN to extract features and then long short-term memory,	Feature learning via CNN outperforms handcrafted features in SMM classification, Including temporal dynamics of the signal using LSTM improves the detection rate
Goncalves et al., 2012	5	5	0	RGB-D, Microsoft Kinect™ sensor and gesture recognition algorithms	30 Hz	Lab	3-15 years (sex not reported)	Not reported	Dynamic time warping	Kinect™ sensor detected 83% of the stereotypical movements.
Torres et al., 2016	4	304	301	Functionnal MRI	0.3 Hz - 1.5 Hz	Lab	6-50 years (269 males, 35 females in the ASD group and 247 males, 54 females in the control group)	ADOS	Gamma PDF, Kruskal–Wallis test	Specific noise-to-signal levels of head movements as a biologically informed core feature of ASD

WASI : Wechsler Abbreviated Scale of Intelligence ; ADOS : Autism Diagnostic Observation Schedule ; ADI-R: Autism Diagnostic Interview, SRS: Social Responsiveness Scale, RBS-R : Stereotyped Behavior Subscale of the Repetitive Behavior Scale-Revised, CARS: Childhood Autism Rating Scale, DSM: Diagnostic and Statistical Manual of Mental Disorders, PDF: Probability Density Functions, SMM: stereotypical motor movements, MRI: magnetic resonance imagery, CNN: convolutional neural network, SVM: Support Vector Machine

Table 2: **Automatic assessment of Gait**

Author name	**Evidence (1: best ; 5: worst)**	**ASD**	**Control**	**Technology used**	**Frequency**	**Setting**	**Sociodemographics of the participants**	**Clinical assessment**	**Statistical /machine learning methods used to analyse the data**	**Main results of the study**
Nobile et al, 2011	3-4	16	16	Infrared cameras (optoelectronic technique with passive markers)	100 Hz	Lab	6-14 years (12 males and 4 females in each group)	DSM-IV-TR, ADOS, ADI-R, WISC-III-R	ANCOVA, correlation	Shorter stride legth and wider step width and a marginally slower velocity. The range of motion in the hips and knees was significantlty reduced, stiffer gait in which the usual fluidity of walking is lost
Longuet et al, 2012	4	11	9	Automatic motion analyser (VICON system) with six cameras having a sampling frequency of 200 Hz	200 Hz	lab	6-13 years (sex not reported)	PEP-R, CARS	ANOVA, Kruskal–Wallis one-way analysis of variance on ranks	Smaller and slower steps. Movement of the head, shoulders and hips were more variable in children with ASD
Eggleston et al, 2017	5	10	0	Eight-camera motion capture system (120 Hz, Vicon Motion Systems)	120 Hz	Lab	5-12 years (6 males, 4 females all ASD)	DSM-IV criteria only	Model Statistic technique	Unique lower extremity joint asymmetries
Calhoun et al, 2011	5	12	22	Eight camera motion capture system and four force plates (Vicon MCam motion capture system) Twenty reflective markers	60 Hz	Lab	5 to 9 years (10 males, 2 females in the ASD group and 10 males, 12 females in the control group)	Not reported	ANOVAs and Kruskal–Wallis tests	Difference for cadence, peak hip and ankle kinematics
Chester et al., 2012	5	12	22	Eight camera Vicon motion capture system and four Kistler force plates	60 Hz for cameras and 600 Hz for forces plates	Lab	5 to 9 years (10 males, 2 females in the ASD group and 10 males, 12 females in the control group)	Not reported	MANOVAs	No asymetry differences during walking
Noris et al., 2006	5	11	11	a motion capture system with 14 fluorescent markers are applied to the joints of the lower body of the child as well as to the shoulders and neck	not reported	Lab	4-10 years (9 males, 2 females in each group)	Not reported	Echo state network (a form of reccurent neural network), PCA	Accuracy of classification of 91% using only half of the complete walk cycle provides good results already
Ilias et al., 2016	5	12	32	16 passive bilateral reflective plug-in-gait (PIG) markery	Not reported	Lab	6-12 years (sex not reported)	Not reported	Neural network and SVM	Accuracy of classification of 95 % and sensitivity of 100% and a specificity of 85 % for the SVM
Hasan et al., 2017	5	24	24	Eight-camera (Vicon T-series) motion capture and two force plates	100 Hz for cameras and 1,000 Hz for forces plates	Lab	4-12 years (18 males, 6 females in ASD group and 12 males, 12 females in the control group)	Not reported	t-tests and Mann-Whitney U tests, Linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA)	LDA classifier with kinetic gait features as input predictors produces better classification performance with 82.50% of accuracy and lower misclassification rate.
Torres et al., 2016	4	3	11	Weak electromagnetic field created by the sensing system (Polhemus Liberty, Colchester, VT, USA) recording	240 Hz	Lab	10-12 years old (3 males in the ASD group) and 5-19 years old (5 females and 6 males) in the control group);	DSM-5, ADOS, ADI-R, MSEL, Vineland	They estimated the parameters of the continuous gamma family of probability distributions and calculated their ranges. These estimated stochastic signatures were then mapped on the Gamma plane to obtain several statistical indexes for each child	Typical walking signatures are absent in all children with ASD. They found an excess noise, a narrow range of probability-distribution shapes across the body joints and a distinct joint network connectivity pattern.
Rinehart et al., 2006	4	11	11	GAITRite Walkway (electronic walkway with pressure sensors embedded in a horizontal grid)	200 Hz	Lab	4-7 years (8 males, 3 females in each group)	DSM-IV, DBC, ADI-R, WPPSI-R, WISC-III	Coefficient of variability, t-test	Greater difficulty walking in a straight line, reduced stride regularity (i.e., adjusted ataxia ratio) with increased variability in velocity, and the coexistence of variable stride length and duration.
Rinehart et al., 2006	3	20	10	Clinical Stride Analyzer (electronic foot-switch in each shoe (i.e., under the sole of the participant's feet)	80 Hz	Lab	6-14 years (4 females, 16 males in the autism group and 2 females and 8 males in the control group)	DSM-IV criteria, ADI-R, IQ	ANCOVA	Increase of stride-length variability in their gait in comparison to control and Asperger participants, both clinical groups were rated as showing abnormal arm posturing, however, only the Asperger's group were rated as significantly different from controls in terms of head and trunkposturing.

Table 2: **Automatic assessment of Gait**

Author name	Evidence (1: best ; 5: worst)	ASD	Control	Technology used	Frequency	Setting	Sociodemographics of the participants	Clinical assessment	Statistical /machine learning methods used to analyse the data	Main results of the study
Hasan et al., 2017	5	15	25	Two force plates were used to measure the 3D ground reaction forces data during walking.	1,000 Hz	Lab	4-12 years (11 males, 4 females in the ASD group and 12 males, 13 females in the control group)	Not reported	Time-series parameterisation techniques were employed to extract 17 discrete features from the 3D ground reaction forces waveforms. t-test and Mann-Whitney U test, stepwise discriminant analysis to select features, three-layers neural network	91.7% accuracy, 93.3% sensitivity and 90% of specificity
Steiner et al., 2012	5	26	0	4 digital camcorder (PAL) : Ariel Performance Analysis System	60 Hz	Lab	10-13 years old (12 males and 14 females in the ASD group)	PAC	time-series analysis (displacement function) and part of the gait cycle (stance and swing phase). The third method was measured joint angles in each plane	The length of the gait cycle become more stable in the sagittal plane for children with riding therapy
Steiner et al., 2015	5	26	0	4 digital camcorder (PAL) : Ariel Performance Analysis System	60 Hz	Lab	10-13 years old, (12 males and 14 females)	PAC	T-probe, paired T probe, chi-squares, Mann–Whitney test, ANOVA	The length of the gait cycle became significantly more stable in the sagital plane after the therapy

ADI-R: Autism Diagnostic Interview-Revised, ADOS: Autism Diagnostic Observation Schedule, CARS: Childhood Autism Rating Scale, DBD: Developmental Behaviour Checklist, DSM: Diagnostic and Statistical Manual of Mental Disorders, ICBS: Infant and Caregiver Behavior Scale, M-CHAT: Modified Checklist for Autism in Toddlers, MSEL :Mullen Scales of Early Learning, PAC: Pedagogical Analysis and Curriculum, PEP-R : Profil Psycho- Educatif (PsychoEducational Profile—Revised), WISC: Wechsler Intelligence Scale for Children, WPPSI: Wechsler Preschool and Primary Scale of Intelligence,

Table 3: **Automatic assessment of motor coordination and hand dexterity**

Author name	Evidence (1: best ; 5: worst)	ASD	Control	Technology used	Frequence	Setting	Sociodemographics of the participants	Clinical assessment	Statistical/machine learning methods used to analyse the data	Main results of the study
Crippa et al., 2015	4	15	15	Infrared cameras (3-D optoelectronic SMART system)	60 Hz	Lab	2-4 years old (12 males and 3 females in ASD group, 13 males and 2 females in control group)	DSM-5, ADOS, Griffiths mental development scales	ANCOVA, Fisher discriminant ratio, SVM	The machine-learning method was able to successfully classify participants by diagnosis. The classification accuracy reached a maximum accuracy of 96.7% (specificity 93.8% and sensitivity 100%) by using seven features selected by the Fisher discriminant ratio-based technique
Campionne et al., 2016	4	9	11	Infrared cameras (3-D optoelectronic SMART system)	60 Hz	Lab	4-5 years old (7 males and 2 females in ASD group, 7 males and 4 females in control group)	DSM-5 ADOS, WPPSI–III, MABC	Mixed analyses of variance	Kinematics of the grasp component was spared in autism, whereas early kinematics of the reach component was atypical.
Perego et al., 2009	5	10	10	Infrared cameras (3-D optoelectronic SMART system). Markers on shoulder, elbow, medial and lateral position of the wrist.	60 Hz	Lab	2-4 years old in both groups	IQ	SVM	Accuracy of 100% with a soft margin algorithm and an accuracy of 92.5% with a more conservative one
Torres et al., 2013	4	34	44	Motion caption system (Polhemus Liberty, 240 Hz)	240 Hz	Lab	3.5-61 years old (24 males, 10 females in the ASD group and 23 males, 21 females in the control group)	Stanford-Binet, ADOS, GARS	Shape and scale of the Gamma familly of probability distribution	Micromovement assessment could allow to characterize and make subtypes of ASD
David et al., 2009	5	13	13	High impedance load cellplaced orthogonally to each other to capture children pression.	125 Hz	Lab	8-19 years old (2 females and 13 males in each group)	IQ, Social Communication Questionnaire (SCQ)	3-level hierarchical linear model	Participants with ASD demonstrated prolonged latency between grip and load forces, elevated grip force at onset of load force, and increased movement variability.
Wedyan et al., 2016	5	17 HR	15	Magneto-inertial platform worn by infants on their wrists	50 Hz	lab	1-3 years (9 males and 8 females in the HR group ; 8 males and 7 females in the low risk)	High risk infants due to an older sibling with autism	Linear Discriminant Analysis (LDA) to extract features, Support Vector Machine (SVM) and Extreme Learning Machine (ELM) to analyse them	The study shows that the accuracy results that were obtained from part two (insert a ball into a clear tube) in the both classifier (SVM and ELM) Accuracy is 75.0%, and 81.67%, respectively.

Table 3: **Automatic assessment of motor coordination and hand dexterity**

Author name	Evidence (1: best ; 5: worst)	ASD	Control	Technology used	Frequence	Setting	Sociodemographics of the participants	Clinical assessment	Statistical/machine learning methods used to analyse the data	Main results of the study
Wedyan et al., 2017	5	17 HR	15	Wearable sensors and sensors inside shapes	50 Hz	Lab	1-3 years (9 males and 8 females in the HR group ; 8 males and 7 females in the low risk)	High risk infants due to an older sibling with autism	linear discriminant analysis to extract features, SVM and extreme learning machine to analyse them	The maximum classification accuracy for a task that inserts the ball into a clear tube open at both sides with mean accuracy 75.0% and 81.67% with SVMs and ELM respectively.
Marko et al., 2015	4	20	20	Robotic manipulandum	100 Hz	Lab	8–12 years (18 males, 2 females in ASD group, 16 males and 4 females in control group)	ADOS or ADOS-2, ADI-R, WISC-IV	ANOVA, generalized linear model, Chi-squares	Abnormal patterns of motor learning in children with autism spectrum disorder, showing an increased sensitivity to proprioceptive error and a decreased sensitivity to visual error
Cook et al., 2013	4	14	15	Cave-hybrid immersive virtual reality theatre, Vicon motion tracking system, six infrared cameras at 100 Hz and markers on the body	100 Hz	Lab	11 males, 3 females in the ASD group and 13 males, 2 females in the control group	ADOS	ANOVA	Atypical interference effects in ASD
Anzulewicz et al., 2016	4	37	45	tablet (iPad mini)	10 Hz	Home	3–6 years old (25 males an 12 females in ASD group, 32 males and 13 females in the control group)	ICD criteria	Machine learning : ExtraTree, random forest, regularized greedy forest	Greater forces at contact and with a different distribution of forces within a gesture, and gesture kinematics were faster and larger, with more distal use of space. 93% accuracy of classification of ASD children vs controls
Fleury et al., 2013	4	23	20	Wacom Cintiq 15-digitizing tablet and pen	142.8 Hz	Lab	4 -8 years old 3 female in each group)	DSM-IV, ADI-R, ADOS, Stanford–Binet Intelligence Scale-5	Hierarchical linear regression	Children with ASD have an intact ability to consistently produce continuous movements, but increased variability in production of discontinuous movements.
Sparaci et al., 2015	4	16	54	Digitalised pen and tablet (Wacom) with virtual pursuit rotor exercise	25 Hz	Lab	5-11 years old (16 males and no female in ASD group, 28 males and 26 females in the control group)	IQ (Raven's Colored Progressive Matrices task), ADOS, Beery Visual Motor Integration Test	ANOVA	Virtual Pursuit Rotor was harder for children with ASD than for TD controls matched for chronological age and intelligence quotient, but both groups displayed comparable motor procedure learning (i.e., similarly incre- mented their TT). However, closer analysis of CTT, DT, and DP as well as 2D trajectories, showed different motor per- formance strategies in ASD, highlighting difficulties in overall actions planning

DSM: Diagnostic and Statistical Manual of Mental Disorders, ADI-R: Autism Diagnostic Interview Revised, ADOS: Autism Diagnostic Observation Schedule, Movement Assessment Battery for Children (MABC-2), GARS: Gilliam Autism Rating Scale, WISC: Wechsler Intelligence Scale for Children, WPPSI: Wechsler Preschool and Primary Scale of Intelligence, ICD-10 : International Classification of Disease,

Table 4: **Automatic assesment of movement used in social interactions**

Author name	Evidence (1: best ; 5: worst)	ASD	Control	Technology used	Frequency	Setting	Sociodemographics of the participants	Clinical assessment	Statistical/machine learning methods used to analyse the data	Main results of the study
Fitzpatrick et al., 2016	4	9	9	Pendulums using a magnetic motion tracking system (Polhemus Liberty, Polhemus Corporation, Colchester, VT, USA)	100 Hz	Lab	12–17 years old, (8 males, 1 female in ASD group ; 7 males and 2 females in the control group)	DSM-IV-TR, ADOS-2, WASI	ANOVA	Less synchronisation in spontaneous and intentional interpersonal motor coordination than controls
Fulceri, 2018	4	11	11	Wearable magneto-inertial sensor fixed through a support on both child and experimenter right wrists	4 Hz	Lab	5-10 years ; (10 males, 1 female in the ASD group 9 males, 2 females in the control group)	DSM-IV, ADOS , WPPSI	ANCOVAs, t-Tests	Impairment in joint action coordination when they had to rely only on kinematic information. They were not able to pay more attention to the kinematic cues in absence of a visual goal.

Table 4: **Automatic assesment of movement used in social interactions**

Author name	**Evidence (1: best ; 5: worst)**	**ASD**	**Control**	**Technology used**	**Frequency**	**Setting**	**Sociodemographics of the participants**	**Clinical assessment**	**Statistical/machine learning methods used to analyse the data**	**Main results of the study**
Marsh et al., 2013	4	8	15	Rocking chair and magnetic tracking system (Polhemus Fastrak, Polhemus Corporation, Colchester, VT).	60 Hz	Lab	2-8 years old , (8 females, 7 males in the control group)	ADOS, Mullen Scales of Early Learning	ANOVA	Disruption of spontaneous and intentional synchronisation
Delaherche et al., 2013	4	7	14	Single camera placed above the participants	25 Hz	Lab	4-11 years old (6 males and 1 female in the ASD group , 12 males, 2 females in the control group)	ICD-10, Vineland or PsychoEducational Profile-Revised	Mann–Whitney non-parametric tests, SVM classifier, continuous classifiers (SVR)	Features characterizing the gestural rhythms of the therapist and the duration of his gestural pauses were particularly accurate at discriminating between the two groups. The duration of the verbal interventions of the therapist were predictive of the age of the child in all tasks. Furthermore, more features were predictive of the age of the child when the child had to lead the task.
Xavier et al., 2018	4	29	39	Avatar and RGB-D sensor (Kinect™ 1)	25 Hz	Lab	6-20 years old (ASD 21 males, 5 females ; 23 males and 16 females in the control group)	DSM-5, WISC-4, ADI-R	generalized linear mixed model	Interpersonal synchronisation and motor coordination increased with age and was more impaired in children with ASD. Motor control was more impaired in ASD group
Boucenna et al., 2014	4	15	15	Nao robot and RGB	10 Hz	Lab	3-13 years old (13 males and 5 females in the ASD group and 9 males and 6 females in the control group)	ADI-R, Vineland, PEP, the Kaufman Assessment Battery for Children or WISC	Neural network (NN) and learning according to the number of recruited neurons	Learning was more complex with children with ASD compared to both adults and TD children
Guedjou et al., 2018	4	15	15	Nao robot and RGB	10 Hz	lab	3-13 years old (13 males and 5 females in the ASD group and 9 males and 6 females in the control group)	ADI-R, the WISC-IV, lobal Assessment Functioning (GAF)	NN and learning according to the number of recruited neurons	NN needs to learn more visual features when interacting with a child with ASD (compared to a TD child) or with a TD child (compared to an adult).
Bugnariu et al., 2013	5	4	4	12 camera motion analysis system at 120 Hz (Motion Analysis corp, Santa Rosa, CA)	120 Hz	Lab	6-12 years old (all males)	Not reported	Dynamic Time Warping algorithm	Children with ASD have poorer imitation behaviour (higher discrepancy values of imitation based on weighted joint angle contributions) during the dynamic task compared to control group.
Anzalone et al., 2014	4	16	16	Nao robot and RGB-D (Kinect™ 1)	25 Hz	Lab	5- 13 years (13 males, 5 females in the ASD group, 9 males, 6 females in the control group)	ADI-R, Vineland, PEP, the Kaufman Assessment Battery for Children or WISC, GAF	K-means, Wilcoxon Mann Whitney rank-sum test, multivariate regression or a Linear Mixed Model (LMM), Fisher test	In ASD, JA skill depends on the interaction partner, and implies a higher motor and cognitive cost.
Anzalone et al., 2018	4	42	16	Nao robot and RGB-D (Kinect™ 1)	25 Hz	Lab	4-11 years old (37 males and 5 females in the ASD group , 12 males, 2 females in the control group)	ADI-R, WISC, the Kaufman- ABC or PEP-3	Mann-Whitney-Wilcoxon test	Body and head movements, gazing magnitude, gazing directions (left vs. front vs. right) and kinetic energies features confirm the reveal the improvements of children behaviours after several months of training with a serious game.
Martin et al., 2018	4	21	21	computer-vision based head tracking (Zface)	30 Hz	lab	2.5-6.5 years old (17 males, 4 females in ASD group and 14 males, 7 females in the control group)	ADOS, ADI-R, DSM-IV, WPPSI-III or Mullen Scales of Early Learning	ANOVA	Children with ASD exhibited greater yaw displacement, indicating greater head-turning, and greater velocity of yaw and roll, indicating faster head-turning and inclination. Follow- up analyses indicated that differences in head movement dynamics were specific to the social rather than the nonsocial stimulus condition.
Campbell et al., 2019	4	82	22	Visualisation of video on a tablet, computer vision analysis front frontal camera of the tablet	30 Hz	Lab	1.5-2.6 years (17 males, 5 females in the ASD group and 48 Males and 34 females in the control group)	M-CHAT-R/F , ADOS-T, MSEL	t-test, Chi-squared test, Linear model, Cox proportional hazards models, Kaplan-Meier Curves	Only 8% of toddlers with ASD oriented to name calling on >1 trial, compared to 63% of toddlers in the control group (p=0.002). Mean latency to orient was significantly longer for toddlers with ASD (2.02 vs 1.06 s, p=0.04). Sensitivity for ASD of atypical orienting was 96% and specificity was 38%.

DSM: Diagnostic and Statistical Manual of Mental Disorders, ADI-R: Autism Diagnostic Interview-Revised, ADOS: Autism Diagnostic Observation Schedule, WISC: Wechsler Intelligence Scale for Children, WASI : Wechsler Abbreviated Scale of Intelligence, WPPSI: Wechsler Preschool and Primary Scale of Intelligence, ICD-10 : International Classification of Disease, PEP : PsychoEducational Profile-Revised, MSEL: Mullen Scales of Early Learning, M-CHAT-R/F: M-CHAT-R/F Modified Checklist for Autism in Toddlers, Revised with Follow-Up (M-CHAT- R/F), CARS: Childhood Autism Rating Scale, ICBS: Infant and Caregiver Behavior Scale, M-CHAT: Modified Checklist for Autism in Toddlers

Table 5: **Automatic Assessments of movement based on natural settings assessment (accelerometers and home movies)**

Author name	**Evidence (1: best ; 5: worst)**	**ASD**	**Control**	**Technology used**	**Frequency**	**Setting**	**Sociodemographics of the participants**	**Clinical assessment**	**Statistical/ machine learning methods**	**Main results of the study**
Memari et al., 2013	5	80	0	Actigraph GT3X	30 Hz	Home	7-14 years old (55 males and 35 females in the ASD group)	DSM-4-TR, ADI-R	t-test, ANOVA, correlations, linear multiple regression	Substantial reduction in activity across the adolescent years in ASD, particulary less active in school compared to after-school.
Pan and Frey, 2006	5	30	0	Accelerometer	0.25 to 2.50 Hz	home	10–19 years (27 males and 3 girls)	Child/Adolescent Activity Log (CAAL)	t-tests, ANOVA	Elementary youth are more active than the other groups, regardless type of day or time period. There are no consistent patterns in physical activity of youth with ASD according to day or time period.
Bandini et al., 2013	4	53	58	Piezoelectric accelerometer (Actical™)	0.03 Hz	Home	3–11 years (45 males and 8 females in ASD group ; 44 males and 14 in the control group)	ADI-R, Vineland, Differential Abilities Scale	t-tests, chi-square or Fisher	After adjustment for age and sex the amount of time spent daily in moderate and vigorous activity (MVPA) was similar in children with ASD (50.0 minutes/day, and typically developing children 57.1 minutes/day)
Cohen et al., 2013	3	15	15	Camera (home movies)	25-30 Hz	Home	0-1.5 years (10 males, 5 females in the ASD group and 9 males, 6 females in the control group)	ADI-R, CARS, Griffiths Mental Developmental Scale or WISC	generalised linear mixed model	Parents of infants who will later develop autism change their interactive pattern of behaviour by increasing father's involvement in interacting with infants; both are significantly associated with infant's social responses
Saint Georges et al., 2011	3	15	15	Camera (home movies)	25-30 Hz	Home	0-1.5 years (10 males, 5 females in the ASD group and 9 males, 6 females in the control group)	ADI-R, CARS, Griffiths Mental Developmental Scale or WISC, ICBS	Markov assumption, Generalised Linear Mixed Model, non negative matrix factorization	Babies with ASD exhibit a growing deviant development of interactive patterns. Parents of AD and ID do not differ very much from parents of controls when responding to their child. However, when initiating interaction, parents use more touching and regulation up behaviors as early as the first semester
Egger et al. 2018	2*	555 HR	1199	Smartphone camera (iPhone)	30 Hz	Home	1- 6 years old (447 males, 108 females in the high-risk group and 764 males, 435 females in the control group)	M-CHAT	Generalized linear mixed models, Linear regression models	An app-based tool to caregivers is acceptable due to their willingness to upload videos of their children, the feasibility of caregiver-collected data in the home, and the application of automatic behavioural encoding to quantify emotions and attention variables

* : this study was done on a large sample with consecutive patients but the M-CHAT is a screening test and a criterion standard of diagnosis. ADI-R: Autism Diagnostic Interview-Revised, CARS: Childhood Autism Rating Scale, WISC: Wechsler Intelligence Scale for Children, ICBS: Infant and Caregiver Behavior Scale, M-CHAT: Modified Checklist for Autism in Toddlers

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