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Algorithms and robotics allow to describe how we learn handwriting and how to better help children with difficulties

Thesis directed by
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Abstract

Handwriting difficulties are frequent and impairing. However, the assessment of motor learning skills is difficult and limits early stage rehabilitation.

Electronic sensors and algorithms can help to measure motor difficulties more easily and objectively. Electronic tablets, for instance, give access to handwriting features that are not usually evaluated in classical assessments. We describe how such digital features (in static, dynamic, pressure, and tilt domains) allow diagnosing dysgraphia and how they evolve during children development. From a finer analysis, three different clusters of dysgraphia emerge, longitudinal studies will allow to underline different patterns of development that seemingly require tailored remediation strategies.

However, those digital features are not used in the context of conventional pen and paper therapies. It is possible to engage children with typical development in handwriting exercises by asking them to teach a robot to write. We implemented a long-term case study (20 sessions, 500 minutes in total) observing a child with severe Developmental Coordination Disorder who did not progress anymore with a classic pen and paper approach by enriched this setup with various training activities using real-time feedback loops (on tilt, pressure, dynamic, pauses). We show how this new method tackles previous child's behaviors avoidances, boosting his motivation, and improving his motor and writing skills.

This thesis demonstrates how new writing digital features allow the implementation of innovative handwriting remediation interventions, which rely on fostering children's individual adaptation characteristics.

Résumé

Les difficultés d'écriture sont fréquentes et handicapantes. Cependant, les difficultés d'apprentissage moteur, dans leur ensemble, sont difficiles à évaluer, ce qui limite par conséquent une rééducation, nécessaire le plus précocement possible.

Des capteurs électroniques et des algorithmes peuvent aider à mesurer ces difficultés motrices plus facilement et plus objectivement. Les tablettes électroniques par exemple donnent accès à des caractéristiques qui ne sont pas utilisées dans les évaluations classiques. Nous décrivons comment ces caractéristiques (dans les comaines statiques, dynamique, de pression et d'inclinaison) permettent un diagnostic de dysgraphie et comment elles évoluent au cours du développement de l'enfant. Grâce à une analyse plus fine, trois différents clusters de dysgraphie émergent, des études longitudinales permettront de mettre en évidence différents modes de développeement qui devraient nécessiter des prises en charges plus personnalisées.

Cependant, ces caractéristiques ne sont pas utilisées dans le contexte de la rééducation conventionnelle papier-crayon. Il est possible d'engager des enfants avec un développement typique en leur demandant d'enseigner l'écriture à un robot. Nous avons enrichi cette preuve de concept avec des activités permettant des boucles de rétrocontrôle en direct (inclinaison, pression, dynamique, pauses), et mis en place une étude de cas à long terme (20 sessions, 500 minutes au total) avec un enfant avec un trouble du développement de la coordination qui ne progressait plus avec une rééducation classique papier-crayon. Nous montrons comment cette nouvelle méthode permet de diminuer les comportement d'évitement de l'enfant, améliore sa motivation et ses compétences de motricité fine et d'écriture. Cette thèse décrit comment de nouvelles caractéristiques numériques permettent d'implémenter des interventions de rééducation de l'écriture, qui se basent sur une adaptation plus personnalisée aux caractéristiques de l'enfant.

Contents

Remerciements

Chapter 1

Introduction

Electronic sensors and algorithms open new approaches to describe movement and especially handwriting. This could help to better understand how we learn handwriting and develop new approaches in the way we conduct rehabilitation in the children with the most severe difficulties to master this skill during education.

1.1 General objectives

The objectives of this thesis are (1) to evaluate the state of art of motor computing applied in Autism Spectrum Disorder (ASD), a sub-type of neurodevelopmental disorder (NDD), (2) to develop new approaches to detect and describe how children learn handwriting, thanks to electronic tablets and algorithms, (3) to propose new approaches for handwriting rehabilitation with electronic tablets and robotics that could be applied with children with NDD.

1.2 Organisation

Motor development is very important. For some authors, it is our only way to interact with the world. According to Wolpert, "we have a brain for one reason and one reason only, it is to produce adaptable and complex movements, [...] Movement is the only way [we] have of affecting the world around [us]. [...] this brain becomes obsolete in organisms that don't need to move anymore"[1]. Motor development is a complex **endeavor** that follows timely organized steps and exposures to environemental activities both basic e.g., eating, walking) an cultural (e.g., writing).

Some children have an impaired motor development. In this first introductory chapter, we will focus on two types of neurodevelopmental disorders (NDD), i.e., Autism Spectrum Disorder (ASD) and Developmental Coordination Disorders (DCD). Child and adolescent psychiatry, occupational therapy and psychomotricity described the difficulties of development of children with ASD and DCD and ways to rehabilitate them for a long time. However, assessments of these motor abilities are based on clinical semi-quantitative standardised instruments that are time-consuming, require the training of experts and can be subjective.

[1] The real reason for brains `https://www.ted.com/talks/daniel_wolpert_the_real_reason_for_brains`

In the second chapter of this thesis, we conducted a systematic review that shows how electronic sensors can measure and how algorithms can help to describe and classify the variety of these movements in children with ASD. A lot of these experiments were done in laboratory settings and do not reach clinical research standards. However, it is likely that these methods will enable practitioners to distinguish ASD from other motors disorders and allow a better monitoring of children's progress in more ecological settings (e.g., at home or in school).

Motor coordination difficulties specifically manifest during school when the children need to learn handwriting. Actually, handwriting is one of the most difficult set of movements that we need to learn in our lifetime, and we need many years to master it.

In the third chapter of this thesis, we will show how we can use electronic tablets to measure handwriting difficulties (i.e., dysgraphia) of children by extracting computational features. These features allow to classify automatically dysgraphia thanks to a random forest algorithm with a good accuracy.

In the fourth chapter of this thesis, we will see how these features develop in both typical development (TD) children and children with dysgraphia and also how they allow a new classification of dysgraphia with three different subtypes found with a K-means algorithm.

These new measures can be used to guide rehabilitation of writing. In the fifth chapter, we will describe the potential of a robot-based approach that can foster the motivation of the participants. We performed a long-term interaction single case study that shows the potential of this approach in clinical practice.

These first experiments, in the field, show the necessity of long-term child-robot interaction that could be more sustainable and efficient by developing social behaviours in the robot. We will present them in discussion.

1.3 Neurodevelopmental Disorders

Neurodevelopemental disorders (NDD) are a group of impairing conditions with onset on the developmental period (i.e., during childhood). They manifest early in the life of children, often before children enter grade school [22]. Their diagnosis is clinical, supported by standardized scales. To facilitate medical decisions, the Diagnostic and Statistical Manual of Mental Disorders-5 (DSM-5) [22] and the International Classification of Diseases (ICD) [275] propose consensual definitions aiming to foster research and communication in medical community. The neurodevelomental disorders are a group of conditions with onset in the developmental period, before the child enters grade school, and are characterized by developmental deficits that produces impairments of personal, social, academic, or occupational functioning. The range of difficulties varies from from very specific limitation of learning or control of executive function [22]. There is a wide heterogeneity of difficulties from specific difficulties to global impairments of social skills and intelligence. Comorbidities (i.e., association of disorders) are frequent, and make heterogeneity of description even larger.

NDD regroup intellectual disabilities, communication disorders, Autism Spectrum disorder (ASD), attention-deficit/hyperactivity disorder, specific learning disorder (e.g., for reading, mathematics), motor disorders (Coordination Disorder, Stereotypic Movement Disorder and Tic Disorders) and other neurodevelopmental

disorders [22]. A recent systematic review showed that despise the lack of medico-economic studies in the field of NDD, the cost of NDD is the highest among all the mental disorders [77].
In this thesis, we will focus on the description of the difficulties children have to learn some movements and focusing on the handwriting. These difficulties are often found in Autism Spectrum Disorder (ASD) and Developmental Coordination Disorder (DCD).

1.3.1 Autism Spectrum Disorder

Autism Spectrum Disorder (ASD) is among the most disabling and studied neurodevelopmental disorders (NDD) in children [344]. It is characterized by impairments in social interaction, communication (loneliness) and restricted and repetitive behaviour (sameness) [22]. The disorder is frequent with a prevalence estimated around 1.5% [229]. Although the onset of ASD symptoms occurs during the first three years of life, the mean age of ASD diagnosis ranges from 38 to 120 months [89, 301, 320]. An early diagnosis is helpful to offer an early intervention and take advantage of a better neuroplasticity [93, 247].

Males are affected 4.2 times more frequently than females [125]. Causes are not completely elucidated and include both genetic (e.g. chromosome 15-q11-q15 duplication) and environmental factors (e.g. foetal valproate exposure) [354]. ASD is a lifetime disorder and its burden continues in adulthood as only a minority of them reach a good outcome and many remain highly dependent on others for support [172]. The cost of ASD for family and society has been estimated between 22,000-28,000 € annualy [171, 207]. The management of ASD consists of early psychotherapeutic treatments based on developmental and behavioural approaches like the Early Start Denver Model [94]. However, these approaches are very time-consuming and a lot of children do not have access to evidence-based care.

Movement abnormalities have been described since the first clinical descriptions of autism by Kanner [198] and Asperger [19] who described patients with "sluggish" reflexes or "clumsy" gait. Meta-analyses have confirmed alterations in motor performances [107, 127] in 85% to 90% of cases [224, 260]. Motor difficulties are significantly correlated to social, communicative and behavioural impairments that define the disorder [110]. Cook et al. argued that movement differences between typical children and those with ASD may contribute to difficulties in reciprocal social cognition [81].

However, motor difficulties do not reach a great attention since repetitive behaviours are the only motor symptomatology included in the current diagnostic criteria of the Diagnostic and Statistical Manual of Mental Disorders-5 (DSM-5) [22] or in the International Classification of Diseases (ICD) [275].

1.3.2 Developmental Coordination Disorder

Developmental coordination disorder (DCD, previously named dyspraxia) is a neurodevelopmental disorder that impairs the acquisition and the execution of coordinated motor skills [22] and perceptual-motor abilities with an impact in daily living and in absence of any physical, sensory or neurological abnormalities. It has a prevalence of 5% in the population [223]. DCD is commonly diagnosed after the age of 5 years highlighted by increasing structured demands of the child's environment [36]. About half of the children with DCD experience difficulties to learn handwriting [158]. Males are affected 2 to 3 times more frequently than females [223]. The symptoms of children diagnosed with DCD persist in adulthood in 30-87% of them [206]. The management of DCD can be divided into two main categories [36]. The bottom-up category with process-oriented (or deficit-oriented) approaches. It assumes that a deficit in a specific body function or sensory process is responsible for the impaired motor skills of children. Its aim is to remediate this underlying process deficit, thereby improving motor performance. The Top-down category contains task-oriented (functional skill) approaches, such as the Cognitive Orientation to daily occupational Performance (CO-OP) [258]. Instead of focusing on a underlying deficit, these approaches involves the children on choosing and training the activities of daily life they need to master. Children are encouraged to think about the nature of the difficulties they encounter and how to find solutions to solve these difficulties [36]. Systematic analysis showed that top-down, task oriented approaches are effective whereas the bottom-up strategies, process oriented are not [36, 296]. However, this data is still limited and should be completed with the most impaired patients that are often not include in these studies. The cost and length of the diagnosis and the rehabilitation make this evaluation difficult and more scalable diagnosis and rehabilitation of these difficulties with new technologies would allow to confirm or not this statement.

1.4 A dimensional approach of Neurodevelopmental Disorders (NDD)

There is a strong relationship between all the NDD. They are very often associated (we call these co-occuring disorders, comordities in the classical DSM-5 and ICD categorical approach). In total, sixty combinations of NDD would be possible. Some authors believe that a common core could be shared by all these disorders [344]. Some clinicians propose a multidimensional approach to overcome the limitations of the categorical approach and comorbidities: Multiplex developmental disorder (MDD), renamed later to the term Multiple Complex Developmental Disorder (MCDD), Multidimensional impairment (MDI), deficits in attention, motor control, and perception (DAMP), or even Early Symptomatic Syndromes Eliciting Neurodevelopmental Clinical Examination (ESSENCE), developmental dysharmony, developmental psychotic dysharmony, or cognitive dysharmony (see Figure 7.3 [386] for a review).

Researchers from the National Institute of Mental Health in United States proposed another approach to bypass the limitations of the categorical DSM-ICD approach: the Research DOmain Criteria (RDoC) (Figure 1.2[2]). This dimensional approach is relevant in child and adolescent psychiatry, especially in neurodevelopmental disorders [134], with a specific perspective taking into account the developmental age [68, 259]. This approach (1) assesses the range of functioning regarding the neurobiological, cognitive and behavioural capacities, representing them along continua of greater or lesser degrees of health or adaptation. This approach as-

[2] retrieved from `https://www.nimh.nih.gov/research/research-funded-by-nimh/rdoc/about-rdoc.shtml`

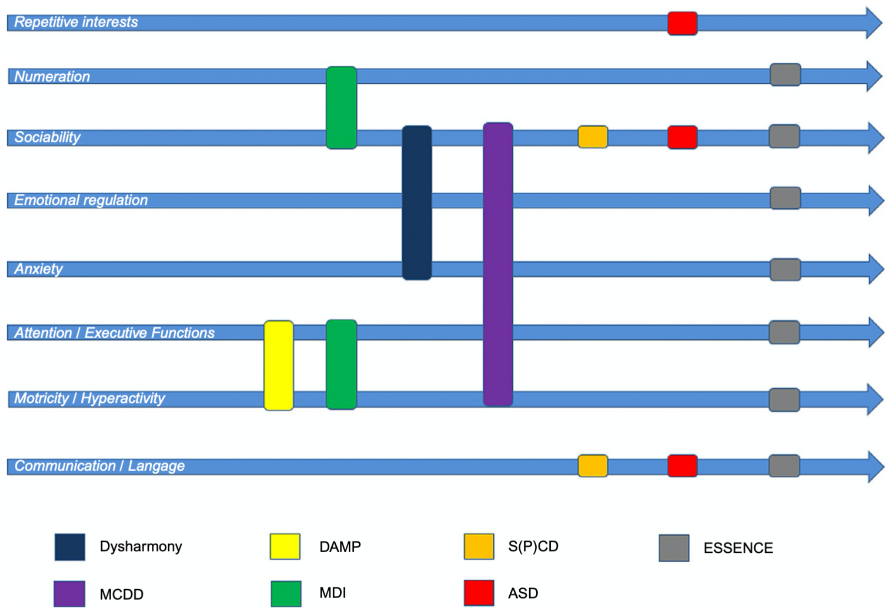

Figure 1.1: Phenomenology and developmental lines in DSM-5 autism spectrum disorder and other complex developmental disorders. ASD, DSM-5 autism spectrum disorder; ESSENCE, early symptomatic syndromes eliciting neurodevelopmental clinical examinations; DAMP, deficit in attention, motor control, and perception; MCDD, multicomplex developmental disorder; S(P)CD, DSM-5 social (pragmatic) communication disorder (Retrieved from Xavier et al., 2020)

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sumes the existence of a continuum between mental health and illness, (2) investigates mental illness through fundamental components of behaviours that cut accross diagnoses. [134]

In this diagnostic approach, tailored for research, it is legitimate to understand motor development, (1) which quality seems to distribute in a continuum of functioning between normal writing and very poor quality and speed and (2) it can be found across categorical diagnoses in several NDD disorders like ASD, DCD, but also Attention-Deficit/Hyperactivity Disorder (ADHD).

In the studies of handwriting (Chapter 2 and 3) presented in this thesis, we will study "Sensorimotor Systems", in particular "Motor Actions" on a behavior and self-report level across different categorical diagnostics.

1.5 Motor difficulties in Neurodevelopmental Disorders (NDD)

Symptoms of Developmental Coordination Disorder (DCD) can be found in ASD [127]. How ASD and DCD interact is still controversial. Regarding motor dysfunction, the DSM-5 now recommends to diagnose them as comorbidities [22]. Some authors support that these two disorders could have similar onset mechanism [146,260]. Others consider the motor dysfunction found in DCD and ASD to be different in nature [286, 387]. In a systematic review, Cacola et al. [57] showed that while DCD and ASD share some behavioural symptoms, distinctions have been shown

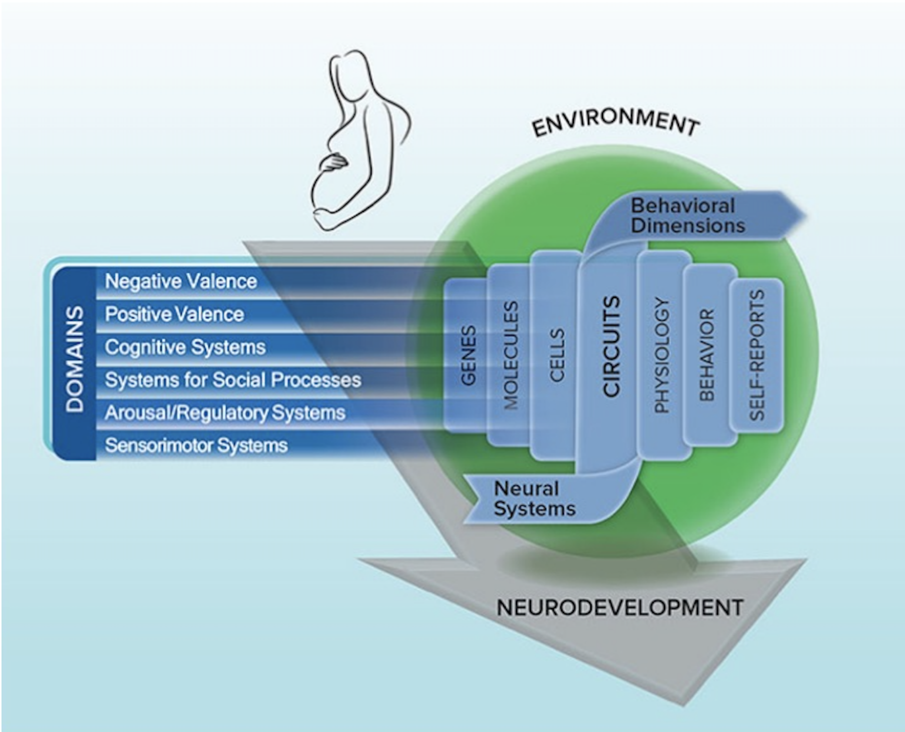

Figure 1.2: Matrix of the Research Domain Criteria (RDoC)

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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) [153, 278].

Clinical assessment of motor coordination is based on semi-quantitative standardized instruments such as the Movement Assessment Battery for Children (MABC-2) [167], the NP-MOT [366], the Test of Gross Motor Development (TGMD-2) [346], the Bruininks-Oseretsky Test of Motor Proficiency (BOT-2) [66], or the Concise Evaluation Scale for Children's Handwriting (BHK) [72] usually done to assess writing. Parental questionnaires are also available such as the DCDDaily-Q [195, 367] or the Dunn questionnaire [109]. For a review of tests to assess DCD, see [6]. However, recommendations for a set of standardized and fixed assessments are difficult since the autism spectrum is large and heterogeneous both in terms of child's commitment with examination and motor dysfunction. Therefore, assessments often require a subjective input from trained professionals, beyond the limitations of being time consuming and tedious to rate. The evaluation sessions regroup several assessments in a row that can be tiring for the child. It does not allow ecological evaluation of the performance in an everyday context. Thus, accessibility of these tests is low and waiting list of 6 months and more is common even in developed countries [164].

1.6 Handwriting difficulties

Handwriting is an essential skill, since children spend up to 60% of their time at school writing [248]. Despite a broad use of laptops and tablets in schools, handwriting remains a paramount skill to be acquired during childhood education as it is the basis of core educational activities such as taking notes, composition and self-expression [34, 47, 145]. Appropriately legible and automated handwriting is necessary for the acquisition of other higher-order skills such as spelling and story composition. Handwriting is a complex perceptual–motor task, as it involves attention, perceptual, linguistic and fine motor skills [48,121,246].

Formal handwriting acquisition begins at the age of five years (preschool) and requires about ten years of practice to reach a level of almost complete automation [38,73,97,121,316,326,374,391]. During this time, handwriting initially evolves on a quality level (from first to fifth-Grade) [3, 72, 159] and then on a speed level (handwriting speed mainly evolves starting from the fourth grade) [232, 326]. Interestingly, a gender effect has been observed in handwriting acquisition, with girls presenting slightly higher quality and speed scores versus their male peers [72], although no effect of handedness has been reported thus far.

Despite education exposure, 5% to 10% of children never reach a sufficient level of automation in handwriting [72, 343]. These handwriting difficulties, termed dysgraphia, affect legibility and/or speed and can seriously impact both children's behavioural and academical development [34].

With the rising cognitive demand of school work, these children quickly face more general difficulties. As they encounter trouble to automatize their handwriting, they cannot handle simultaneous tasks such as grammar, spelling, or composition. This leads to an increase of fatigue and decrease of cognitive performance and self-esteem [214, 322]. To avoid accumulation of school difficulties, it is of prime importance to detect and remediate these handwriting difficulties as early as possible [76, 121].

Given the prerequisites of handwriting acquisition, dysgraphia can be related to language problems, motor learning and/or motor execution, visual-motor problems, coordination problems, or cognitive impairments (e.g., attention deficit). In consequence, dysgraphia can be observed in the context of various NDD such as dyslexia, developmental coordination disorders, or attention deficit disorders with or without hyperactivity (ADHD) [90]. Dysgraphia is not recognised by the Diagnostic and Statistical Manual of Mental Disorders, fifth edition (DSM-5) [22] or the International Classification of Diseases 11th edition (ICD-11) [1] as a disorder per se, but can be a specifier of neurodevelopmental disorders. Most classifications of dysgraphia suggest three sub-groups and are usually based on comorbidities. For example, Deuel (Table 1.1 [103]) proposed to differentiate: (1) dyslexic dysgraphia that is often comorbid with attention-deficit or dyslexia; (2) spatial dysgraphia that is the consequence of a defect in the understanding of space; and (3) motor dysgraphia that is often comorbid with a DSM-5 motor acquisition disorder.

Assessing the legibility or readability of handwriting is not a new challenge, as studies relating to this topic exist since the beginning of the twentieth century. The first scaling method was developed by Thorndike in 1910. This constituted a very important contribution "not only to the experimental pedagogy but to the entire movement for the scientific study of education". Thorndike compared his invention to the thermometer. "Just as it was impossible to measure temperature beyond the

Dyslexic dysgraphia	Spontaneously written text is poorly legible, with textual complexity influencing legibility
	Oral spelling severely abnormal
	Copying of written text relatively preserved
	Drawing relatively preserved
	Finger-tapping speed normal
Dysgraphia due to motor clumsiness	Spontaneously written text is poorly legible
	Oral spelling relatively preserved
	Copying of written text poorly legible
	Drawing usually compromised
	Finger-tapping speed abnormal
Dysgraphia due to defect in understanding of space	Spontaneously written text is poorly legible
	Oral spelling relatively preserved
	Copying of written text poorly legible
	Drawing severely abnormal
	Finger-tapping speed normal

Table 1.1: Clinical classification of dysgraphia proposed by Deuel [103]

very hot, hot, warm, cool, etc., of subjective opinion, so it had been impossible to estimate the quality of handwriting except by such vague standards as one's personal opinion that given samples were very bad, bad, very good, etc." [23]. Until now, two approaches are used to evaluate handwriting. The first is a global holistic method that evaluates the handwriting quality as a whole, while the second measures it according to several predefined criteria.

Many quantitative tests were proposed to evaluate penmanship. Most quantitative methods assess handwriting according to several predefined specific criteria. The judgment is made by experts grading these criteria and summing the sub-scores. A number of tests using this principle have been developed for different alphabets.

The presence of dysgraphia can be assessed via different tests in different alphabets [20]. Concerning the Latin alphabet, we can use the Detailed Assessment of Speed of Handwriting (DASH) [28]; the Ajuriaguerra scale (E scale) [97]; and the Concise Evaluation Scale for Children's Handwriting (BHK) which is the gold-standard test in France for diagnosing dysgraphia. Initially developed in the Netherlands [159], the BHK has since been adapted for use in other languages including French (Charles et al [72]). Importantly, as all of these tests are conducted using a pen/pencil and paper, their scoring is restricted to the analysis of the final, static handwriting product and does not consider or include any information about the movement dynamics.

	Validation number	Age range [y.o.]	Test duration [min]	Scoring duration [min]	Alphabet	Language	Number of items	Dynamic of handwriting	Pressure	Tilt	Speed	Posture	Writing task
Ajuriaguerra [158]	350	6-12	2	5	Latin	French	37	✗	✓*	✗	✓	✓	WT1
BHK [159]	837	6-12	5	10	Latin	Multi-language	13	✗	✗	✗	✓	✗	WT2
BHK-teenager [277]	471	12-18	5	10	Latin	Multi-language	9	✗	✗	✗	✓	✗	WT2
DASH [28]	546	9-16	20	10	Latin	English	5	✗	✗	✗	✓	✗	WT3
HHE [116]	230	6-18	5	0	Hebrew	Hebrew	10	✗	✗	✗	✗	✗	WT4

Table 1.2: Resume of different tests used to diagnose dysgraphia. WT1: Copy a sentence several times, request of quality and speed, WT2: Copy a long text for 5 min, WT3: Copy a sentence several times, alphabet, geometric figures and composition, WT4: Copy a text containing all letters. *some pressure aspects of handwriting are assessed thanks to carbon paper.
Ajuriaguerra scale (E scale): is a well spread test evaluating the quality of the writing depending on speed and precision. It had a special focus on the posture and style of pen grasping of the child.
Concise Evaluation Scale for Children's Handwriting (BHK): is the gold standard test to diagnose dysgraphia in Latin alphabet based language [158, 200, 277].
BHK for teenagers: has also been created using the same principles.
Detailed Assessment of Speed of Handwriting (DASH test): evaluates the quality and the speed of the writing in different conditions (quality, speed, writing with a free topic of the child choice).
Hebrew Handwriting Evaluation (HHE): that examines Hebrew handwriting products and assess the legibility through both global and analytic measures.

In Table 1.2, we summarize the different tests widely used to diagnose dysgraphia. As shown, these tests are heterogeneous as they were specifically designed to assess the handwriting quality for a specific alphabet or a specific age range. Moreover, we can see that these tests are based on handwriting from different writing tasks (see columns core task in Table 1.2), which might imply high variability of the results. Finally, an important part of the information is not taken into account. Only the final product of handwriting is used for analysis, disregarding the handwriting dynamic, tilt, and, in most cases, the pressure.

One of the main drawbacks of these tests is that the scoring of several parameters relies on human judgment which makes the test more subjective. Moreover, grading of the BHK test is also time consuming since scoring can take up to 15 minutes. Additionally, as the expert responsible for the scoring only has access to the final static image of the child's handwriting, some very informative handwriting aspects, such as the handwriting dynamics, the pressure between the pen and the tablet or the pen tilt remains hidden and are, therefore, not used in the diagnosis. In the same way, posture and grasping style are difficult to assess and must be done live by an expert evaluator. Finally, the text used in the test is standardised (the content of the text is always the same). Consequently the test cannot be performed during ecological writings sessions (e.g., during schools sessions with the text actually written everyday by the child). Re-assessment of writing with the same tool could cause over-learning (the performance during the test is improved because the child become trained to perform always the same task, such as writing this same words) but could not generalize to other texts for instance.

The rapid development of digital tablets in the last decade partially allowed us to tackle some of these problems. It made possible the evaluation not only the final product of handwriting (static image) but also its dynamic. New features become accessible including the pressure between the pen and the tablet's surface as well as the pen's tilt. Recent studies point that pressure features are useful in the diagnosis of dysgraphia [312].

The difficulties in handwriting could self perpetuate due to avoidance and anxiety. We propose a model composed of two vicious loops (Figure 1.3). The one on the left is self amplified by an avoidance of the writing stimulus via a negative reinforcement mechanism [342]. The avoidance in the short-term decreases anxiety but in the long term increases the anxiety and decreases self esteem. The second vicious loop, shown on the right, is the consequence of the lack of training. The lack of training, itself decrease the writing training opportunities that themselves limits the improvement of writing. In the end, the anxiety generated by the practice and the lack of practice induce a mismatch between what the child can do and what parents and teachers expect from him/her.

Concerning rehabilitation, recent reviews and some professionals recommand simple graphomotor exercises focusing on the primitives of writing (loops, bridges, etc.) can tackle the avoidance which is frequent in these children. Then, with exercises more and more complex, depending on the child performance and motivation eventually leading to training in writing [36].

Meta-analyses showed that remediations of writing ($>$ 1 month) including handwriting practice, and not only relaxation or sensory-based training, are the most efficient approach [173].

A good clinical evaluation based on the anxiety and the motivation of the child

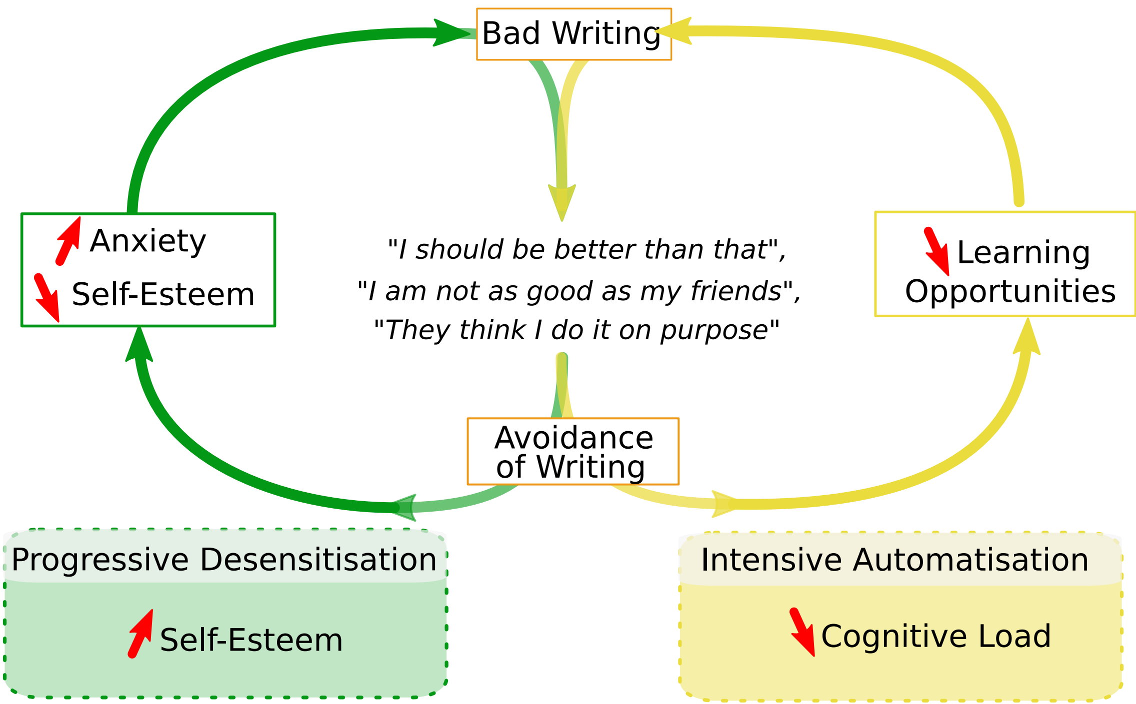

Figure 1.3: Functional analysis of writing difficulties maintenance. Vicious circles can appear due to anxiety (left) and lack of practice (right), that can worsen handwriting. Adapted from [70, 85]. A recent empirical network approach is trying to better conceptualize how differents psychological and biological factors are deeply intertwined in feedback loops [42, 43]. Below, possible strategies to break the vicious circles.

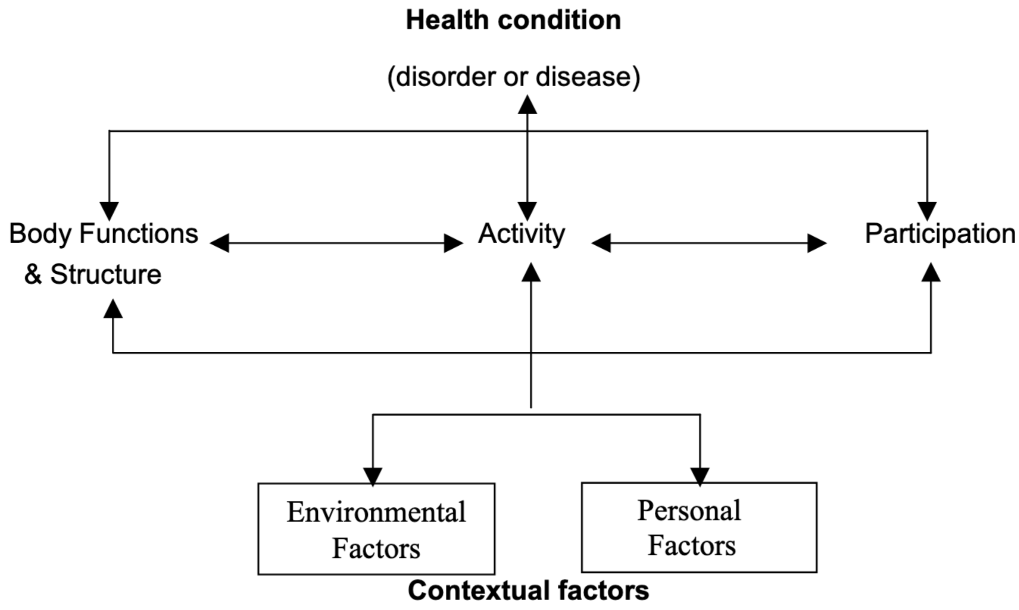

Figure 1.4: Model of disability used for the International Classification of Functioning

throughout the exercises could help to tailor the rythmn remediation targetting the final goal (handwriting) without increasing anxiety.

The research on disability is very important in this situation since the handwriting itself is not compulsory in our life and can be bypassed without too many consequences. According the world health organization, the disability is the conjunction of the environment with the person (Figure 1.4 [274]). Some adaptations in the environment can help to bypass the difficulties expressed by the child. Thus, it is possible to decrease the handwriting requests of children with handwriting difficulties, educating the parents and teacher about the difficulties [174][3], by providing them printed copy of the class material, favor oral evaluation, training the use of laptops for the oldest children, use of specific softwares[4]. These adaptations allow to decrease the disability in the case rehabilitation is not efficient or possible. In practice, both strategies can be proposed in parallel during the care of children with dysgraphia.

Motor difficulties are frequent and impairing. To improve, the access and the precision of the evaluation of motor learning skills, we propose to use electronic sensors and algorithms. In the next chapter, we make a systematic review of the assessment of motor disorders with such technologies, focusing on the example of Autism Spectrum Disorders (ASD).

[3]https://www.cartablefantastique.fr/la-dyspraxie/quest-ce-que-la-dyspraxie/
[4]https://www.cartablefantastique.fr/outils-pour-compenser/comment-compenser/

1.7 Training in Child and Adolescent Psychiatry (CAP)

Due to the high prevalence (i.e., frequence) and cost of these NDD, it is important to train enough professionals, to limit the impact of the disabilities in these children, and to improve their inclusion in the family and the society. However, recruitment into Child and Adolescent Psychiatry (CAP) was found to be problematic in two-thirds of 28 European countries [340], which indicates that CAP training is not perceived as an attractive option to most European medical students [340]. This supports the argument that more efforts needs to be done to raise overall CAP training standards [340] and junior doctors' job perspectives. Non-pharmaceutical approaches (like psychotherapy) are the main approaches in NDD. Nonetheless, we showed in an online survey that, in Europe, the training in psychotherapy is poor for both adult, and child psychiatrist, even if (1) the motivation to train is high [133], and (2) the field is diverse and active[5]. To improve the training and attract more professionals, online learning, especially Massive Open Online Courses (MOOC), could be a good support since: (1) this population, being already educated with a general background in medicine and psychiatry, is more likely to stay engaged [105], (2) online learning offers more flexibility to young professionals spending most of their time in the hospital. Furthermore, this online resources can be useful for teachers with NDD pupils, other education professionals and parents. We can find general introduction about CAP[6], and specialised courses about ASD[7]. We recently conducted a survey about a Cognitive-Behavioural Therapy MOOC[8]. It showed that it was feasible, even with a practical content like psychotherapy [131]. The drop-out was less important than in other MOOCs, maybe due to the high educational background of participants [83]. Changing the scale of education, from a classical classroom to online learning, is not trivial, and requires a specific organization [105]. Recent methods based on the results of (1) gaze analytics [336], (2) other learning analytics [41] or even (3) role-plays with avatars[9] could enhance motivation and learning outcomes of MOOCs.

[5] https://epg.pubpub.org/
[6] https://iacapap.org/essentials-of-child-and-adolescent-psychiatry-across-the-world/
[7] https://www.coursera.org/learn/troubles-spectre-autisme-diagnostic
[8] https://elearning.europsy.net/
[9] https://ict.usc.edu/prototypes/miles/

Chapter 2

Innovative assessment of motor disorders

Parts of this chapter are submitted and under review in Cognitive computation journal, under the title ”Automatic assessment of motors impairments in Autism Spectrum Disorders: a systematic review”.

Abstract

Introduction

Autism spectrum disorder (ASD) is mainly described as a disorder of communication and socialisation. However, motor abnormalities are also common in affected individuals. New technologies may offer quantitative and automatic metrics to measure movement dysfunctions.

Objectives

We sought to identify computational methods in order to automatize the assessment of motor impairments in ASD.

Methods

We systematically searched IEEE (Institute of Electrical and Electronics Engineers), Medline and Scopus databases using terms including 'autism', 'movement', 'automatic', 'computational', and 'engineering' and reviewed the literature from 2000 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, or which focused on computational models of movement but also eye tracking, facial emotion or sleep.

Results

In total, we located 54 relevant articles that explored static and kinetic equilibrium, like posture, walking, fine motor skills, motor synchrony and movements during interaction that can be impaired in individuals with autism. These studies employed several devices to capture relevant motor information as cameras, 3D cameras, motion capture systems, accelerometers. Interestingly, since 2012, the number of studies increased dramatically as technologies became less invasive, more precise, and more affordable. Open-Source and in-house softwares have enabled the extraction of relevant data and 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.

Conclusion and implications of key findings

Movement computing opens new perspectives for patient assessment in ASD research, enabling precise characterizations in experimental and at-home settings. It is likely that these methods will 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).

2.1 Introduction

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 [22]. The disorder is highly prevalent, estimated to affect around 1.5% of the population [229]. Although the onset of ASD symptoms occurs during the first three years of life, the mean age at the time of ASD diagnosis ranges from 38 to 120 months [89,301,320]. An early diagnosis is necessary to ensure an early intervention that takes advantage of higher neuroplasticity [93, 247].

Males are affected 4.2 times more often than females [125]. Causes are not completely understood and include both genetic factors, as the chromosome 15-q11-q15 duplication, and environmental factors as foetal valproate exposures [354]. ASD is a lifetime disorder and its burden continues in adulthood as only a minority of affected individuals achieve reasonable outcomes and many remain highly dependent on others for support [172]. ASD is often associated with other NDDs, such as attention-deficit/hyperactivity disorder, tic disorders, developmental coordination disorder) and comorbidities (e.g., anxiety disorder, epilepsy [244]. Thus, the heterogeneity is large.

Movement abnormalities have been discussed since the first clinical descriptions of autism made by Kanner [198] and Asperger [19] who described patients with 'sluggish' reflexes or a 'clumsy' gait. Meta-analyses have confirmed alterations in motor performances exist [107, 127] in 85% to 90% of cases [224, 260]. Motor difficulties are significantly correlated with social, communicative and behavioural impairments that define the disorder [110]. Cook et al., [81], argued that movement differences between typical children and those with ASD may contribute to difficulties in reciprocal social cognition.

However, repetitive behaviours are the only motor symptomatology included in the current diagnostic criteria of the *Diagnostic and Statistical Manual of Mental Disorders*, fifth edition (DSM-5) [22] and in the *International Classification of Diseases*, 11$^{\text{th}}$ edition [275]. Symptoms of developmental coordination disorder (DCD) can be found in ASD [127]. 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 [22]. Some authors support the existence of different disorders that could be caused by the same mechanisms [146, 260]. Others consider the motor dysfunctions found in DCD and ASD to be different in nature from one another [286, 387]. In a systematic review, Cacola et al. [57] showed that, while DCD and ASD share some behavioural symptoms, distinctions exist in terms of gestural performance, the 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 [153, 278].

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) [167]; the NP-MOT (Neuro-Psychomotrian evaluation of the child) [366]; the Test of Gross Motor Development (TGMD-2) [346]; the Bruininks-Oseretsky Test of Motor Proficiency (BOT-2) [66]; or the Concise Evaluation Scale for Children's Handwriting (BHK) [72], which usually performed to assess writing skills.

Parental questionnaires are also available, including the DCDDaily-Q [195, 367] and the Dunn questionnaire [109]. For a review about tests to assess DCD, see Albaret et al. [6]. However, recommendations for a set of standardised and fixed assessments are difficult since the autism spectrum is large and heterogeneous both in terms of a child's commitment to an examination and their 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, which can be tiring for the child to complete. Further, such assessments do not allow for an ecological evaluation of their performance in an everyday context. Thus, the accessibility of these tests is low and a waiting list of six months or more is commonly seen, even in developed countries [164].

Computational technologies offer the opportunity of going beyond these barriers, 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) assessment of neuro-developmental milestones achieved by humans from birth onwards" [61, 62]. Applications are numerous and include robotics ([46,192,203,331]), computer games ([149]), diagnosis ([27, 164, 203]) and behaviour imaging [11, 12, 355]. Machine learning techniques, as Convolutional Neural Network (CNN) [389] in particular, are more and more used in medicine [362]. 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) [265]; in the assessment of social behaviors in ASD with contact-less and irritation-free sensors [210]; in the analysis of data from questionnaires and interviews [335]; opening to new, fascinating approaches as in [315], 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, [257] such as in dementia [180] or Parkinson, [117] as characterization tool, but also for the development of new treatments, as the ones based on brain-computer interfaces [237]. In this context, a review focusing on the assessment of motor difficulties in children with autism seems 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 in interaction from one another.

2.2 Method

We search systematically the Institute of Electrical and Electronics Engineers (IEEE) [1], Medline [2] and Scopus [3] databases from January 2000 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.

2.2.1 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 [177]. We also excluded eye-tracking studies (see Papagiannopoulou [282] for a systematic review), emotion expression studies focusing in facial action units in laboratory settings (see El Kaliouby et al [115] for a review), driving assessment (see wilson et al. [381] for a review) and sleep assessments (see Moore et al [262] for a review) since these points were tackled by reviews cited above. We excluded studies that did not include children since the variability with adults can be great.

2.2.2 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 [339]; study design, in terms of the number of subjects included and the existence of a control group; automatic system used to identify ASD peculiarities; sampling frequency; type of setting (i.e., experimental laboratory vs. natural 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 [22]. The report was complied according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [261].

[1]https://ieeexplore.ieee.org/Xplore/home.jsp
[2]https://www.ncbi.nlm.nih.gov/pubmed/
[3]https://www.elsevier.com/solutions/scopus

2.3 Results

In total, we identified 54 relevant articles dealing with new technologies, motor behaviours and including children with ASD. Figure 2.1 details the process and output for studies selection and inclusion. The included studies were quite heterogeneous as they explored different movements that can be impaired in ASD and measured automatically 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 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 2.2). 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.

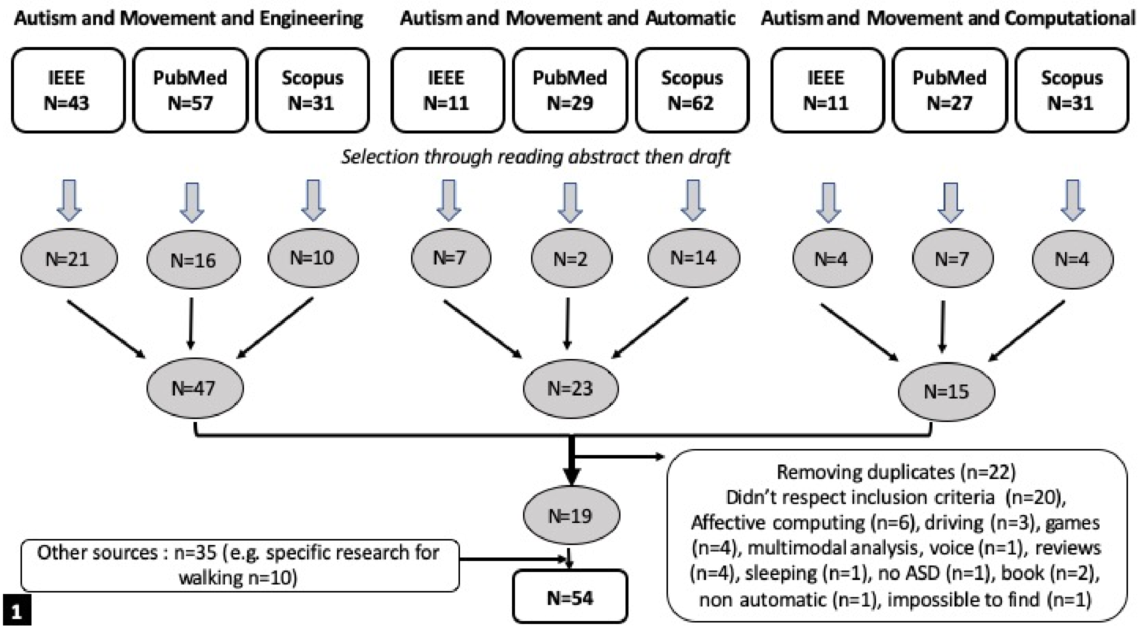

Figure 2.1: Flowchart of study inclusion

2.3.1 Equilibrium (N = 24)

Tonus

Hypotonia and ligamentous hyperlaxity are often described in children with ASD [157,256,337]. In a population-based study [334] as well as a retrospective analysis of parents' early concern [153], a low muscle tone in infancy predicted autistic traits or ASD. However, among children, a disharmonious tonic typology may be encountered with a hypertonic component for the muscles of the trunk and the proximal muscles of the lower limbs and a laxity component for the ankles and the proximal and distal muscles of the upper limbs (wrists and shoulders) [285]. However, we didn't find any distinct method used to automatically assess the tonus.

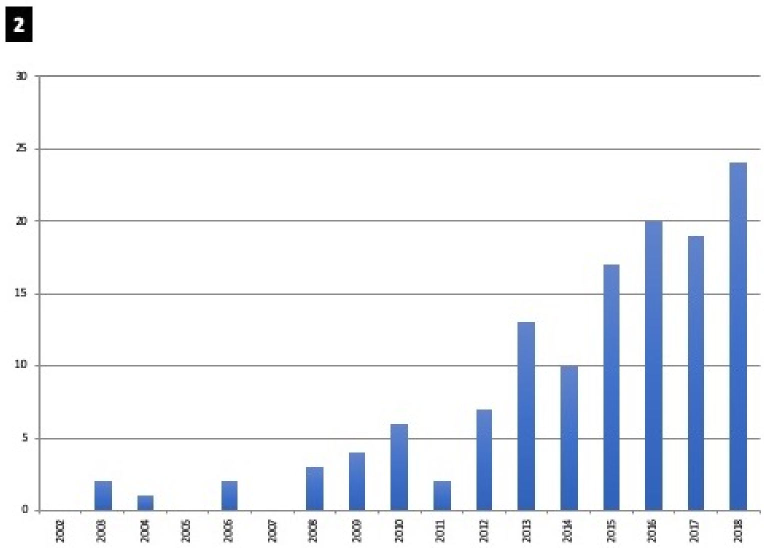

Figure 2.2: **Number of publications found in PubMed (Medline) according to the search terms 'autism' AND 'movement' AND ('automatic' OR 'computational' OR 'engineering')**

Posture analysis (N = 10, Table 1)

Posture instability is common in children with ASD (for reviews see [222,350]), with an increase in the size of the support polygon and shorter strides [270] noted that can lead to lead to difficulties like holding up its own heads, sitting and walking [184].

Assessment with consumer devices

Travers et al. [360] 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 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.

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 wearable and 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 [7, 142, 143, 255]. 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 but allowed to assess stereotypical movement in ecological environments like classrooms.

Elsewhere, Rad et al. [298–300] used wireless inertial sensing technology to detect

Figure 2.3: Sensors used to assess posture in ASD:
Nintendo Wii balance board™ (A); Kinect™ (RGB-D sensor) (B).

stereotypical motor movement 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 can be 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 [140, 141] 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 Kinects but the latter does not require the child to wear any device or marker.

Resting state during magnetic resonance imaging

Torres et al. examined the noise-to-signal ratio of micro-movements present in time-series of head motions extracted from resting-state functional magnetic resonance imaging scans of 304 children with ASD and 304 control group children [356]. Based on complex pretreatment and data analysis, the authors hypothesized the existence of micro-movements as potential biomarkers of ASD.

Gait (N = 14, Table 2)

The walking pattern appears to be altered in people with ASD [370, 371]. Several abnormalities have been described in ASD including toe-walking [376], variable stride length and duration, incoordination, head and trunk positionning abnormalities during walking, reduced plantar flexion, and increased dorsiflexion [58] (for an in depth review see Kindregan et al. [205]). During our research, we found 14 studies investigating the gait difficulties in ASD automatically (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. [270] set up a system composed if eight infrared camera (Elite System™, Bts ® Bioengineering, Milan, Italy). The use of several cameras allowed these authors to limit the limit the extent of the problem of 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. [226] 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. [113] found that children with ASD (N=10) exhibited unique lower-extremity joint asymmetries. Further, Calhoun et al. [58] reported significant differences between children with ASD (N=12) and controls (N=22) regarding cadence, and peak hip and ankle kinematics. However, Chester and Calhoun [75] did not find any differences in asymmetry during walking between the two study groups.

Attempts to automatize the diagnosis

Noris et al. [272] measured a collection of three-dimensional coordinates from 14 markers applied to the joints of the lower-body area of 11 children with ASD and 11 controls using an infrared cameras (motion-capture). Using an echo state networks (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. [181] 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. [162] 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 [357] used a motion caption 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.

Pressure systems

Rinehart et al. [304] asked 11 children with ASD and 11 controls to walk on a GAITRite Walkway (CIR Systems Inc., Franklin, NJ, USA) and observed a greater level difficulty was experienced by children with ASD regarding walking along a straight line and dealing with the coexistence of variable stride length and duration.

Figure 2.4: The clinical stride analyser

Children with ASD were also less coordinated and rated as more variable and inconsistent (i.e., they showed reduced smoothness) relative to the comparison 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 [303]. 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. [163] 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 (N=25) individuals, especially throughout the first half of the stance phase. Specifically, they showed a higher maximum braking force, lower relative time to maximum 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 [347, 348] used a gait analyser constructed based on 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, 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 study set-ups were quite precise, achieving classification models with high accuracies. However, such studies required trained teams, their costs were high, the activities recorded were highly specific and the generated models seemed difficult to be generalized to ecological scenarios.

2.3.2 Fine motor skills requiring hand dexterity and visuo-motor coordination (N = 12, Table 3)

Young children with ASD have poorer fine motor skills in tasks like object handling, grasping and visual-motor tasks [189, 297]. 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 [284, 295]. Children with ASD also display differences in movement planning and execution [238].

Grasping (N = 9)

Sacrey et al. [318] 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 [87] 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 [60] used the same system showing that children with ASD (N=9) took a longer time to complete the whole reaching movement. Kinematics of the grasp component were spared in autism, while early kinematics of the reach component were atypical. During a grasp and throw task with a ball, Perego et al. [291] 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. [82] asked participants with ASD (N=14) to participate in a biological motion perception task in which 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 TD 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 can’t 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 [62]. 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 [92].

Wedyan and Al-Jumaily [378, 379] 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). Elsewhere, Marko et al. [240] 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 sensed through vision and proprioception. Children with ASD outperformed typically developing children (TD) when learning from errors that were sensed through proprioception, but underperformed TD children in comparison when learning from errors that were sensed through vision.

Pointing

Torres et al. [355] 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 to the study performed a two pointing tasks; one without and one with a decision-making 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.

Touching and drawing (N = 2)

Anzulewicz et al. [15] 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) among 15 children with ASD. Children with ASD showed an intact ability to consistently produce continuous movements, but an increased degree of variability in the production of discontinuous movements [124].

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 [122]). 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 [20]. However, Sparaci [345] showed that a virtual pursuit rotor exercice [2] with a pen on a tablet was harder for patients with ASD than for controls to perform.

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

Monitoring movements in ASD is important since social interaction difficulties are required symptoms for its diagnosis. Affective computing [115] 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 [369].

Motor coordination or synchrony (N = 4)

Fitzpatrick et al. [123] 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. [130] 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 [241].

Cameras or cameras with a depth sensor (RGB-D camera) have been used to evaluate motor turn-taking and motor synchrony. Delaherche et al. [100] 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 therapist and the duration of their gestural pauses were particularly accurate at discriminating between patients with ASD (N=7) and controls (N=14).

Interpersonal distance

In general, interpersonal distance is larger among children with ASD [63, 136, 308, 364]. However, sometimes, children with ASD can position themselves very close to other people, violating others' personal space [202]. 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 [4], as the open access libraries OpenPtrack [5], 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 children are isolated and stay far from the others or not.

Motor imitation (N = 4)

Social deficits in ASD have been linked to imitations difficulties [308]. Motor imitation has been investigated by NDE in several protocols. Xavier et al. [387] used

[4] https://www.epfl.ch/labs/cvlab/research/research-surv/research-body-surv-index-php/

[5] http://openptrack.org/

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 TD 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. [44] and Guedjou et al. [151] developed a robotic interactive system in which a child imitates the robot's motor postures and then the robot imitates the child's motor postures based on a camera. The system was able to extract a motor signature indicating when interacting with children with ASD (N = 15) as compared to TD controls (N = 15) or adults. The system required more computational power, i.e., more neurons in the neuron networks to achieve posture recognition in autistic personnes than with TD chilren. [151].

Bugnariu et al. [52], showed that children with ASD (N=4) had poorer performances while imitating a robot than TD 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 because its ability of matching the temporally inexact nature of imitation.

Joint attention (N = 2)

Impairment in joint attention (JA) is a key symptom of ASD that appears early in development [96]. 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 [191]. 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 [11], proposing new metrics able to describe it through head pose and posture [12].

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 [242]. 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 didn't 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. 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

[6] http://zface.org/

seconds, p=0.04) [59].

2.3.4 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.

Accelerometers (N = 2)

Accelerometers were first used in the assessment of sleep among children with ASD [380]. By putting a GT3X device (Actigraph, Pensacola, FL, USA) on the right hip for seven consecutive days, Memari et al. [252] showed a reduction in physical activity in ASD participants during the adolescence. However, Pan and Frey and Bandini [25, 281] did not observe any difference in physical activity.

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 [353], while others did not replicate this result [278]. Many analysis have been conducted by manually annotating videos, as in [16, 280]. 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 as instance while showing shared attention (for a review see Saint Georges et al. [319] and Costanzo et al. [84]). Infant motor symmetry and gait were explored by Maestro et al. [233–235]. Infants who went on later to develop autism showed more asymmetry and gait dysfunction than TD children. Using the same Pisa home movie database, Cohen et al. [78] and Saint-Georges et al. employed a computational analyses of synchrony [321] and a motherese classifier [236] to refine assessments of early interaction. They showed specific patterns of early caregiver-infant interaction in those who go on to develop autism.

Recently, Egger et al. [112] 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 the face behaviours, they identified significant differences in emotion and attention according to age, sex, and autism 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. [169], 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.

2.4 Discussion

2.4.1 Main findings

Campollo coined the term 'neurodevelopmental engineering' to refer to the development of hardware that would help to assess stereotypies and motor difficulties in

ASD. This is a rapidly evolving area of research that could help to facilitate more objective evaluations especially during screening, but also an improved understanding and monitoring of the development of children with ASD or other neurodevelopmental disorders [95, 325]. Beside stereotypies, this review shows that many motor activities can be tracked automatically in ASD with a good level of sensitivity. Authors exploited such techniques founding differences between children with ASD and controls in all the domains of movements, obtaining sometimes high levels of accuracy while using automatic classification. In other studies, the proposed techniques allowed the detection of stereotypical motor movements.

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) [55]. Some of these devices can allow the capture of large amounts of ecological data, while being cheap, availables in the consumer market with a reasonable price. With time, they will became less invasive, more affordable and the more and more available for ecological contexts.

The number of studies collecting data in natural environments has been usually modest, due to the challenges they face in their completion. However, thanks to new technologies, such studies become more and more feasible. Assessment using tablets (writing, touching, pointing), as 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 accessible 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 the partial control of the environment they offer, together with the possibility of collecting structured data.

Giving 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 these specific 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 [20]). 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 could not be a good strategy to investigate relevant markers of development since other evaluations are easier to do in ecological settings at an earlier stage.

The different computational methods employed in the explored studied 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 movement, improving the interpretability of the obtained models. Other teams have employed 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. Some data analysis strategies permitted feedbacks in real time whereas for others their computational cost is higher and such feedbacks are not feasable. Some of these algorithms have made it possible the use of less-

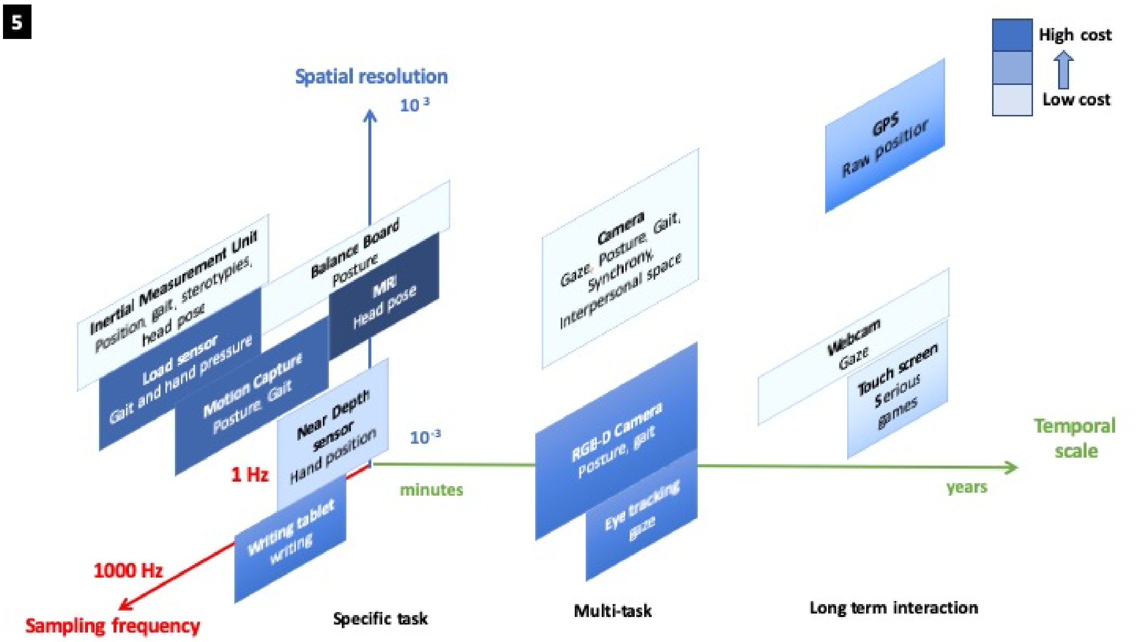

Figure 2.5: Properties of motion sensors in terms of sampling frequency, spatial resolution and temporal scales of use

invasive and more accessible devices, as the tracking technologies that do not use body markers, (a simple camera could be sufficient): OpenFace [112] instead of an eye-tracker or OpenPose (Figure 7A) instead of a motion capture system.

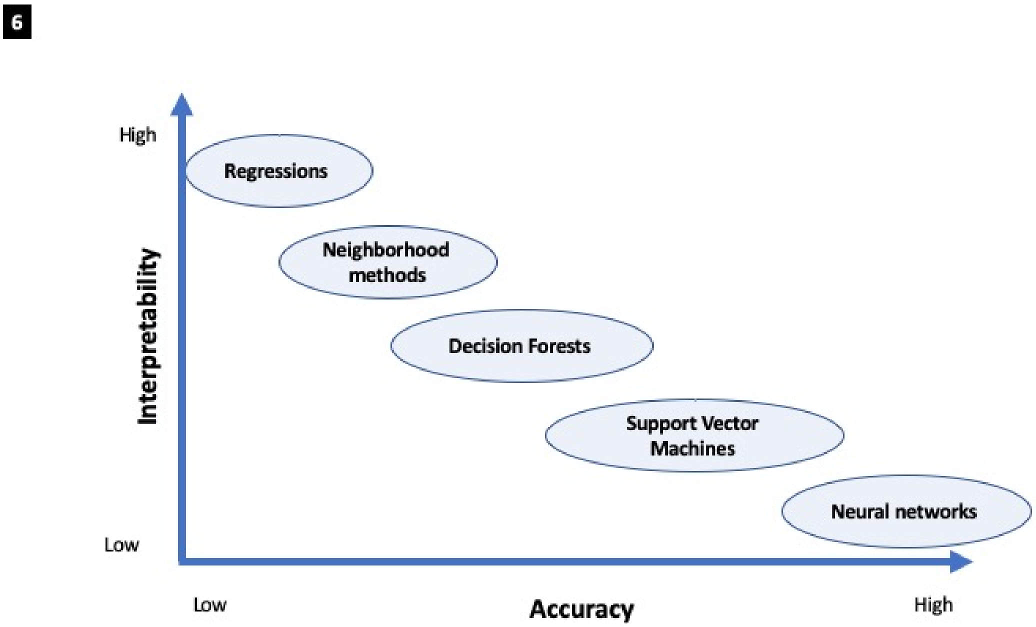

Figure 2.6: Properties of main machine learning methods in terms of interpretability and accuracy

2.4.2 Limitations

The quality of evidence obtained in the explored studies does not reach the clinical standard for routine diagnostic assessment. Most of the studies do not report on how to limit the risk of bias. 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 [228]. The highest medical standards would require the recruitment of large series of consecutive patients. An open science framework with accessible data and software will enable easier replications in different populations to increase the generalisation of the results [264].

There is a lack of cognitive models to bridge the gap between cognitive sciences and NDE. From a theoretical point of view, futures research should combine with computational approaches to ASD [144,352]. Some authors (eg. [358]) in particular, believe that integrating a perception-action perspective would be fruitful since the movement production in ASD has been linked to a movement-perception deficit, which is preliminary to the understanding of intentions, posture, and facial expressions and thus social abilities and communication.

Large datasets would require 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 instance, a database of positions built using the global positioning tracking system or another one built exploiting home movies or data from smartphone [112] or either some technologies would need the transfer of sensitive data away to more powerful machines, can surely lead to discussions about privacy. 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 the field.

2.4.3 Perspectives

We think that movement computing [269] aimed at automatically measure 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) [138]. We think that the technologies here outlined will allow the achievement of this goal. Behavioural assessment could help in identifying more homogenous endophenotypes.

Several teams [15, 355, 388] 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 [355]. 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, cultural movements as writing that could involve different cerebral computations and thus lead to different difficulties.

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 items, in order to adapt a special posture for further evaluation. Other systems could allow the development of adapted behaviours by a robot from interactions with a child [290].

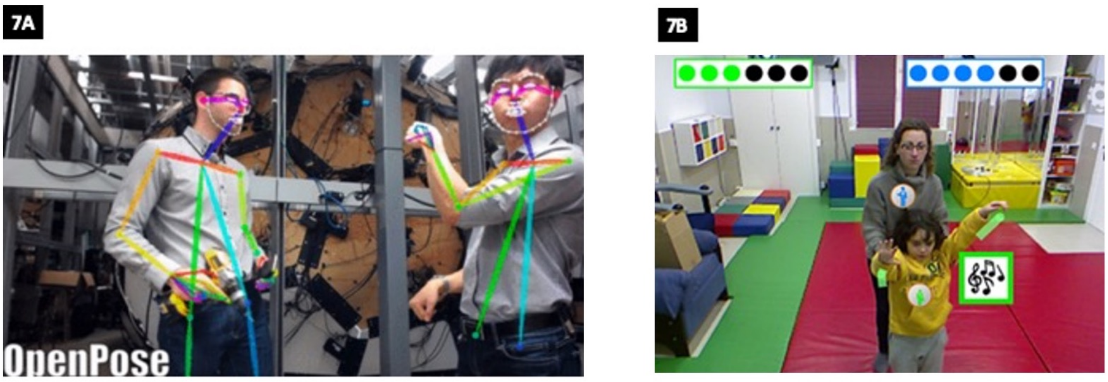

Figure 2.7: Screenshots from the use of Open Pose (A) and from the serious game Pictogram Room (B)

2.5 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 collecting standardised large amounts of movement data to better understand the specificities of movement disorders in ASD and to enable descriptions to allow for the screening and identification of more objective endophenotypes.

In the following chapters, we will take the specific example of handwriting. These difficulties are frequent and not only found in ASD. It is one of the most difficult and usual movement one's need to master through lifespan. It can be recorded via electronic tablets that give new insight on the handwriting thanks to feature extractions and easy-to-interprete models like regression models, neighbourhood methods (K-means) and Decision forest (Random Forest). After this analysis part, we will show how we used openpose during rehabilitation that enable the meaure of body pose with a simple camera and a Neural Network.

2.6 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 2.1: **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, micro-controller 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 hand-crafted features in SMM classification, Including temporal dynamics of the signal using LSTM improves the detection rate

Table 2.1: **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**
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 2.2: **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.

Table 2.2: **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**
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 assignificantly different from controls in terms of head and trunkposturing.
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

Table 2.2: **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**
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 2.3: **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.
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

Table 2.3: **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**
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 performance 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 2.4: **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.
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 nonparametric 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).

Table 2.4: **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**
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 2.5: **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 TD 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

Chapter 3

An automatic handwriting diagnosis

Parts of this chapter are published, under the title "Automated human-level diagnosis of dysgraphia using a consumer tablet" [20]. Asselborn, T., Gargot, T., Kidziński, Ł., Johal, W., Cohen, D., Jolly, C., Dillenbourg, P. (2018). Automated human-level diagnosis of dysgraphia using a consumer tablet. NPJ digital medicine, 1(1), 1-9.

Some aspects of this chapter were discussed in [102] and our response [21]. Some of the points raised are discussed in a following article presented in chapter 4.

Abstract

Introduction

The academic and behavioral progress of children is associated with the timely development of reading and writing skills. Dysgraphia, characterized as a handwriting learning disability, is usually associated with dyslexia, developmental coordination disorder (dyspraxia), or attention deficit disorder, which are all neurodevelopmental disorders. Dysgraphia can seriously impair children in their everyday life and require therapeutic care. Early detection of handwriting difficulties is, therefore, of great importance in pediatrics. Since the beginning of the 20th century, numerous handwriting scales have been developed to assess the quality of handwriting. However, these tests usually involve an expert investigating visually sentences written by a subject on paper, and, therefore, they are subjective, expensive, and scale poorly. Moreover, they ignore potentially important characteristics of motor control such as writing dynamics, pen pressure, or pen tilt. However, with the increasing availability of digital tablets,features to measure these ignored characteristics are now potentially available at scale and very low cost.

Method

In this work, we developed a diagnostic tool requiring only a commodity tablet. To this end, we modeled data of 298 children, including 56 with dysgraphia. Children performed the BHK test on a digital tablet covered with a sheet of paper.

Results

We extracted 53 handwriting features describing various aspects of handwriting, and used the Random Forest classifier to diagnose dysgraphia. Our method achieved 96.6% sensitivity and 99.2% specificity.

Conclusion

Given the intra-rater and inter-rater levels of agreement in the BHK test, our technique has comparable accuracy for experts and can be deployed directly as a diagnostics tool.

3.1 Introduction

The rapid development of digital tablets in the last decade allowed us to extract new features and thus have access to new features hidden so far. It made possible the evaluation not only of the final product of handwriting (the static image), but also its dynamics. For instance, Esposito et al, used handwriting and drawing features from a Wacom tablet to see difference in motor performance according to Big Five Personality questionnaire [118].

It is also possible to tackle partially some of the limitations of tests to diagnose dysgraphia. Multiple studies have employed these new technologies to better understand writing disabilities. Pagliarini et al [279] used tablets to collect data on handwriting ability before handwriting is performed automatically. Quantitative methods allowed them to find patterns indicating potential future writing impairments at a very early age. Mekyska et al. [250] used a Random Forest model to classify dysgraphic children. The authors included 54 third-grade Israeli children in the study and used a 10-item questionnaire for Hebrew handwriting proficiency (HPSQ) [310] to identify poor writing. In the adult population, automatic handwriting assessment tools we reproposed for Parkinson's Disease as a potential biomarker [108]. In this work, we build on previous work in order to design a digital diagnostic tool. Compared to previously established results,we focus on clinical relevance in pediatrics. To this end, we analyzed data for children who have been clinically diagnosed with dysgraphia, and matched them with a cohort of children with typical development. We maximized the potential impact of the work by focusing on the Latin alphabet—the most popular script worldwide, which is used by approximately 2.6 billion people.Moreover, we defined features related to those currently used in clinical practice. Our quantitative model leverages four categories of writing characteristics: the geometrical aspect of handwriting, and the use of pressure, tilt, and kinematics. We used a Random Forest classifier to predict dysgraphia. In the test set,approximately 96% of dysgraphic writers were labeled correctly(true positive ratio), while less than 1% of non-dysgraphic children were incorrectly diagnosed (false negative ratio). We obtained an F1-score of 97.98%.

After building the model, we explored and analyzed the most important features for the diagnosis of dysgraphia. In this analysis,we combined statistical analysis and collaboration with clinicians,exchanging examples and comments. The conclusions were then used to provide insights for the development of a new screening tool that would modernize the current gold-standard test, BHK.

	Dataset	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5
Age (Std.) in years	**TD**	6.77 (0.29)	7.80 (0.30)	8.75 (0.27)	9.85 (0.35)	10.90 (0.38)
	D	6.83 (0.10)	7.92 (0.67)	8.97 (0.53)	10.08 (0.67)	10.98 (0.61)
Males/Females	**TD**	23/26	22/29	21/20	22/26	28/25
	D	2/0	14/6	9/3	14/1	7/0
Right handed/Left handed	**TD**	41/8	48/3	38/3	41/7	46/7
	D	2/0	16/4	11/1	13/2	7/0

Table 3.1: Summary statistics of the participants involved in this study

3.2 Materials and methods

3.2.1 Participants

The present study was conducted in accordance with the Helsinki Declaration. It was approved by the Grenoble University Ethics Committee (Agreement No. 2016-01-05-79). It was conducted with the understanding and written consent of each child's parents, the oral consent of each child,and in accordance with the ethics convention between the academic organization (Laboratoire de Psychologie et NeuroCognition (LPNC)—Centre National Recherche Scientifique) and educational organizations.

A total of 242 Typically Developing (TD) children were recruited in 14 primary schools from various Grenoble suburbs to ensure differing socio-economic environments (*TD dataset*). Children from the first to fifth grade were recruited from 43 classes. None of the TD children included in the study presented known learning disabilities or neuro-motor disorders.

The study also included 56 dysgraphic children (*D dataset*) recruited at the Learning Disorders Clinic of Grenoble Hospital (Centre Referent des Troubles du Langage et des Apprentissages, Centre-Hospitalier-Universitaire Grenoble). They were all diagnosed as dysgraphic based on their BHK scores. The scores were assigned by a single rater.

In order to validate the analysis on the combined dataset of D and TD, we needed to compare age distributions in both groups. The Kolmogorov–Smirnov test showed no statistical difference (p=0.32) in terms of ages between the two distributions (D and TD datasets). Based on this result and the qualitative assessment of the Q–Q plot (see Figure 3.1), we concluded that there was no evidence of a difference between these two distributions and they could be treated jointly in the analysis.

For more information concerning the participants, we refer the reader to Table 3.1.

3.2.2 Data collection

The 298 children (TD dataset + D dataset) involved in this study performed the BHK test by writing on a sheet of paper affixed to a Wacom graphic tablet (sampling frequency=200 Hz; spatial resolution=0.25 mm). A Wacom Intuos 4 tablet was used for the TD set, and a Wacom Intuos 3 for the D set. Pressure data were carefully calibrated between the two tablets. The BHK test consists of copying a text for 5 min. The first five sentences of the text are composed of monosyllabic words typically learned during first grade. Then the complexity of the words starts increasing. Scoring includes two dimensions: (1) handwriting velocity, calculated by counting the number of characters written; and (2) handwriting fluency, which takes into

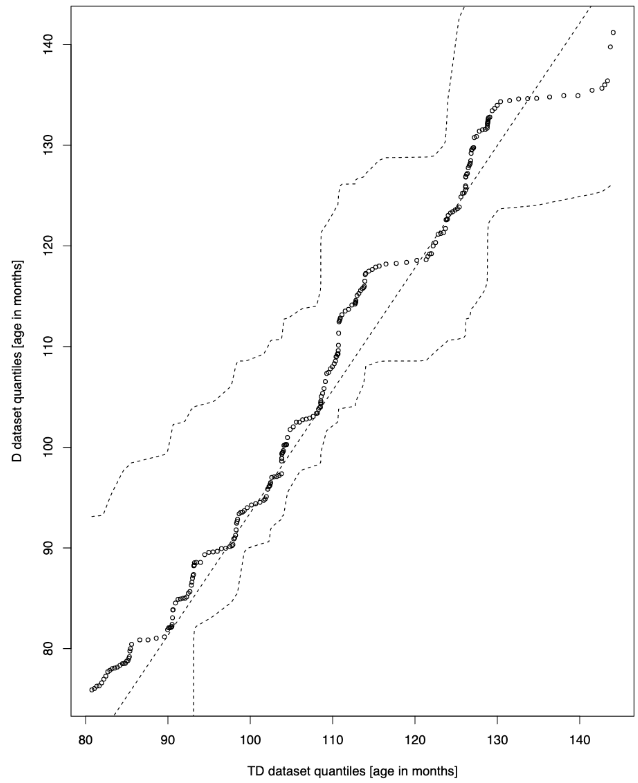

Figure 3.1: Quantiles of the TD dataset (x-axis) against the quantiles of the D dataset (y-axis). The points are closed from the diagonal dashed line and included in the confidence bounds, showing the similarity of the two distributions.

account only the first five sentences of the text and is assessed semi-quantitatively according to 13 clinical features (see Table 3.2 for details on the features used). The data was collected using Ductus software (LPNC laboratory) [154]. Doing so allowed children's handwriting parameters to be saved, including the x and y coordinates, pressure, and tilt of the pen, for every time frame at a maximum sampling rate of 200 Hz. In addition, the age, gender, and laterality of the writers were saved.The BHK tests of the dysgraphic children (D dataset) were rated by one expert from the hospital in Grenoble. None of the BHK tests from the TD dataset were rated for dysgraphia, which means that some of these children might be dysgraphic, as well.

3.2.3 Features extraction

In this work, we tried to extract the spectrum of features that could describe handwriting in terms of different aspects, such as static, dynamic, tilt, and tremors.

We organized all the features into four categories:

- Static features—purely geometric characteristics of a written text.
- Kinematic features—dynamics of handwriting path.
- Pressure features—characteristics of the pressure recorded between the pen tip and the tablet surface.

	BHK Item	Corresponding Feature
Letter	Variation in Height of Small Letters (a, c, e, i, m, n, o, r, s, u ,v, w, x)	✗
	Incorrect Relative Height of letters	✗
	Distorted Letters	✗
	Ambiguous Shapes of Letters	✗
Text	Handwriting Size	Handwriting Size
	Margin Shifted to the Right	✗
	Non Linear Lines	Moment of Handwriting
	Words too Narrowed	Space Between Words
	Chaotic Writing (trace not fluid, too many change of directions during handwriting)	Median of Power spectral of Tremor Frequencies*, Bandwidth of Tremor Frequencies*, Median of Power Spectral of Speed Frequencies*, ...
	Loss of Links between Letters	In Air Time Ration*, Std. of Speed*, Std. of pressure*, ...
	Superposed Letters	Handwriting Density*
	Modified Letters	Handwriting Density*
	Shaky Handwriting	Bandwidth of Tremor Frequencies, Median of Power spectral of Tremor Frequencies

Table 3.2: Mapping between the extracted features and the BHK items. *represents features which are not mapped directly to the BHK item but which are likely to explain a similar concept. The category of the BHK features is written in the left column.

	Feature	t-stat	p-value	Mean *TD*	Std. *TD*	Mean *D*	Std. *D*
Static	Moment of Handwriting	2.02	**0.045**	-25.02	73.45	-0.93	89.14
	Handwriting Density	2.10	**0.037**	84.48	42.40	99.31	65.36
	Space Between Words	-5.62	$\mathbf{5.36 \cdot 10^{-8}}$	0.0049	0.0016	0.0031	0.0029
	Handwriting Size	-2.89	**0.0042**	3686.53	1213.11	3145.91	1222.67
	Bandwidth of Tremor Freq.	5.92	$\mathbf{1.14 \cdot 10^{-8}}$	$3.00 \cdot 10^{-3}$	$3.92 \cdot 10^{-4}$	$3.36 \cdot 10^{-3}$	$3.86 \cdot 10^{-4}$
	Median of Power spectral of Tremor Freq.	5.81	$\mathbf{2.02 \cdot 10^{-8}}$	$3.18 \cdot 10^{-3}$	$1.77 \cdot 10^{-4}$	$3.32 \cdot 10^{-3}$	$1.03 \cdot 10^{-4}$
	Dist to mean of Tremor Freq.	3.65	$\mathbf{3.21 \cdot 10^{-4}}$	$2.57 \cdot 10^{-4}$	$1.52 \cdot 10^{-4}$	$3.56 \cdot 10^{-4}$	$2.38 \cdot 10^{-4}$

Table 3.3: A comparison between the two groups of writers (D dataset and TD dataset) for every feature based on the static handwriting features. For each feature, we report the mean and standard deviation in each group as well as the t-statistic and p-value from the comparison between the two groups.

- Tilt features—characteristics of the pen tilt. Every feature used in the analysis is described below

Static features

The design of the BHK and its scoring limit analysis to just the static aspects of handwriting. Each of the 13 BHK features can be classified into one of two categories. The first category regroups features which assess handwriting quality at a letter level. A direct translation of these features requires knowledge of the letter's shape. Since this would require a large-scale analysis of shapes of letters, which would be language-dependent due to variations in the Latin alphabet, we disregarded these features in the analysis. The second category of features focuses on higher-level aspects of handwriting. In this case, we were able to construct features related to BHK concepts.In this section, we outline the features engineered for the study. More details on the mapping between the BHK items and our static features can be found in Table 3.2.

Detailed analysis of all Static features can be found in Table 3.3.

Space between words:

The distance (in pixels) between words,averaged for the entire text and logged.

Handwriting density:

A grid with 300-pixel cells covering the entire range of the handwriting trace was created. The number of points in each cell, if present, were stored in an array. The mean value of this array represented our approximation of the handwriting density.

Moment of handwriting:

To compute this feature, we extracted bins of 300 points (from the same line of text) and computed its barycenter. The distance in they direction between consecutive barycenters is computed and averaged for all of the points. This reflects the average direction of the written line, which could be a proxy for the "non-straight lines" item on the BHK.

Handwriting size:

To compute this feature, we extracted bins of 300 points (from the same line of text) and computed the total surface occupied by the box bounding the trace.

Tremor frequencies:

This feature quantifies shaky handwriting. For each child, we first divided the signal into bins of 600 points (as can be seen in Fig. 3.2) and extracted from each of these bins the deviance from the handwriting path. To do so, two types of vectors were extracted, as we present at the top of Figure 3.2: for the first one, we computed a "global" vector by averaging bins of 10 points (represented in green in Fig. 3.2). This vector represents the global direction of the handwriting movement in a restricted area of 10 points. The second vector is local as it is not averaged on bins of points. It simply links points inside this restricted area of 10 points (represented in blue in Fig. 3.2). The cross product of these two vectors tells us how orthogonal the local vector is compared to the"global"vector. The greater the result of this operation is, the higher the deviance from the path is. We conjecture that shaky handwriting will result in local vectors being rarely aligned with their global counterparts and can then be detected with this method. For each of the 600 points, we log the norm of the cross product.

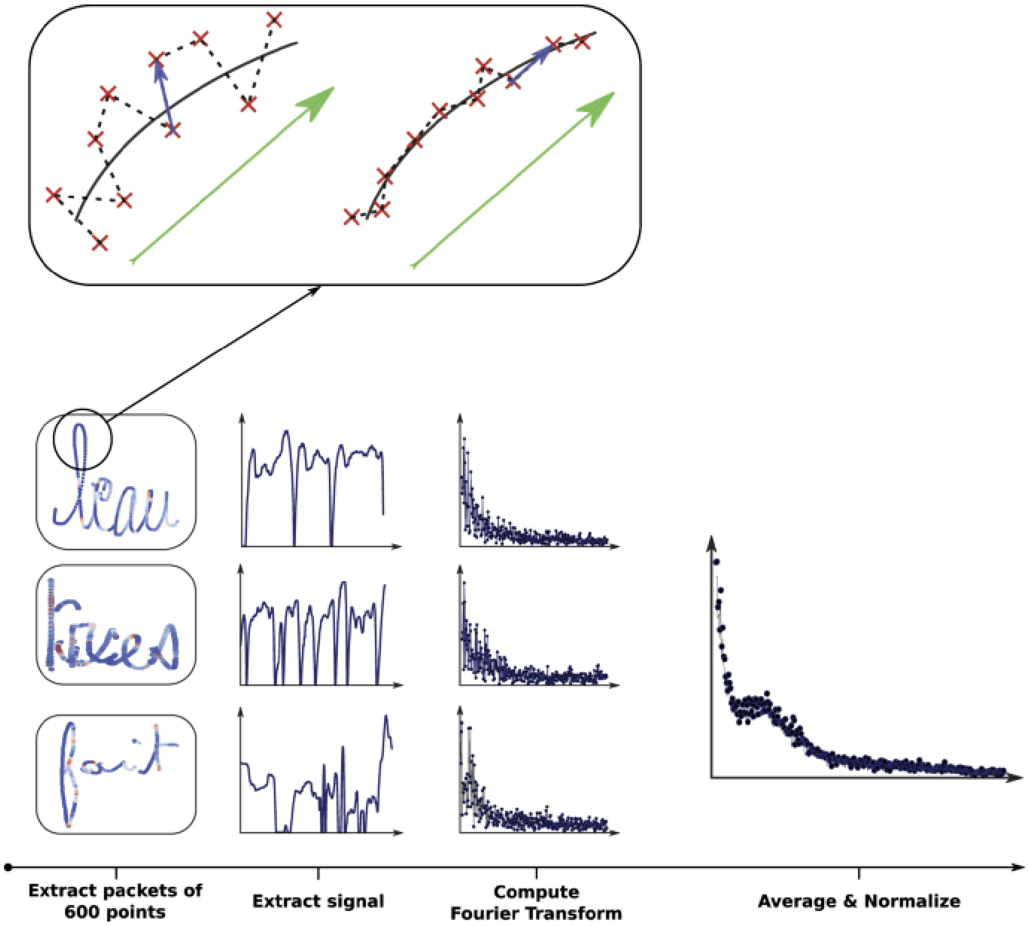

Figure 3.2: The whole process used to extract the frequency spectrum of our signal. (1) We first divided the BHK text into bins of 600 points. (2) For each packet, the signal was extracted. (3) We then computed the Fourier transform of the signal. (4) We took the average of all signals and finally performed a normalization. At the top of the figure is presented an example of a signal extracted from the data: the red dots are the point coordinates recorded by the device during handwriting. The vectors in blue are "local" vectors linking two consecutive points. The vector in green is the "global" vector (average of the nine blue vectors) representing the global direction of the handwriting. The cross product of these two vectors gives us an indication of the smoothness/shakiness of the handwriting. The image on the right comes from a writer with smoother/less shaky handwriting than the one on the left. The cross product operation will detect this difference

	Feature	t-stat	p-value	Mean *TD*	Std. *TD*	Mean *D*	Std. *D*
Kinematic	Mean Speed	-2.23	**0.027**	3.22	1.17	2.81	1.25
	Max Speed	2.81	**0.0054**	20.51	10.22	25.02	11.01
	Std. of Speed	2.17	**0.031**	2.50	0.78	2.78	1.07
	Increase (slope) of Speed	2.54	**0.012**	$1.65 \cdot 10^{-4}$	$3.37 \cdot 10^{-4}$	$3.41 \cdot 10^{-4}$	$6.98 \cdot 10^{-4}$
	Nb of Speed Peaks per secs	-0.70	0.49	0.038	$3.76 \cdot 10^{-3}$	0.037	$2.20 \cdot 10^{-3}$
	Mean Acceleration	-1.37	0.17	0.40	0.17	0.36	0.17
	Max Acceleration	-0.72	0.47	6.17	16.34	4.58	2.12
	Std. of Acceleration	-0.22	0.83	0.43	0.30	0.42	0.17
	Increase of Acceleration	-0.40	0.69	$4.67 \cdot 10^{-5}$	$2.35 \cdot 10^{-3}$	$-8.51 \cdot 10^{-5}$	$1.10 \cdot 10^{-3}$
	Bandwidth of Speed Freq.	20.86	$\mathbf{4.92 \cdot 10^{-55}}$	$1.20 \cdot 10^{-3}$	$1.97 \cdot 10^{-4}$	$2.19 \cdot 10^{-3}$	$5.24 \cdot 10^{-4}$
	Median of Power Spectral of Speed Freq.	21.49	$\mathbf{5.12 \cdot 10^{-57}}$	0.0013	$1.83 \cdot 10^{-4}$	0.0021	$3.34 \cdot 10^{-3}$
	Dist to mean of Speed Freq.	8.60	$\mathbf{1.23 \cdot 10^{-15}}$	$2.84 \cdot 10^{-4}$	$1.39 \cdot 10^{-4}$	$5.62 \cdot 10^{-4}$	$3.49 \cdot 10^{-4}$
	In Air Time Ratio	6.94	$\mathbf{3.91 \cdot 10^{-11}}$	0.52	0.075	0.61	0.11

Table 3.4: A comparison between the two groups of writers (D dataset and TD dataset) for every feature based on the handwriting kinematics. For each feature, we report the mean and standard deviation of the two groups as well as the associated t-statistic and p-value for the t-test.

We computed the Fourier transform on the vectors, regrouping the results of all of these cross products. Then, the average of all of the Fourier transforms coming from these different bins of 600 points (see Fig. 3.2) was computed. In this manner, a normalization was finally achieved for every child in our database.

With this analysis, we aimed to quantify the tremor/shaky aspect of handwriting, which would then be translated by higher frequencies or a wider bandwidth in the spectral domain.

For example, we extracted the range of frequencies covering 90% of the spectral density. Our hypothesis is that, the smaller this value is (meaning that the distribution is more clustered), the more proficient the writer is. A writer having a huge bandwidth will not be fluent as they are less consistent in their movements. This feature is called Bandwidth of Tremor Frequencies.

Motivated by this concept, we also extract the median of the power spectral density. A higher value of this feature indicates a higher presence of high frequencies. We refer to this feature as Median of Power Spectral of Tremor Frequencies.

The last feature we define in this context is the distance between the spectral distribution of the writer to the averaged spectral distribution of all the writers in our database. The higher this distance is, the more eclectic the handwriting of this particular writer. This feature is called Distance to Mean of Tremor Frequencies.

Kinematic features

Detailed analysis of all kinematic features can be found in Table 3.4.

Handwriting speed:

We hypothesize that abnormal variability in speed is indicative of handwriting problems. We quantify the speed as the distance traveled by the pen divided by the time taken. Although Wacom data is collected at 200 Hz, we noticed high frequency noise, and, to remedy this issue, we applied a moving average filter with n=10 and then subsampled every 10th point. We only kept the measurement if the penstayed on the surface during the 10 points (no in-air time). Finally, we computed the mean,maximum, and standard deviation for each user. With this technique, we had access to the local handwriting speed every 10 points. We then performed a linear regression to compute the evolution of the handwriting speed. Motivated by insights from clinicians, we also computed the number of speed peaks per seconds. To that end, we applied a Gaussian filter to the signal of velocity over time, and we computed the number of local maxima and minima extracted. We expect that the number of peaks should grow with the total duration of the test, and,therefore, we normalize this number by time.

Handwriting speed frequencies:

We can interpret handwriting as a two-dimensional time series. As such, we can apply common time-series analysis techniques, and, in particular, we compute the Fourier transform. We conducted the process described in Fig.3.2 and then we extracted the Bandwidth of speed frequencies, the Median of power spectral of speed frequencies, and the Distance to mean of speed frequencies.

Handwriting acceleration:

Acceleration is another measure of variability in speed. We computed the mean,maximum, and standard deviation of acceleration following the same procedure as that used to extract the mean, maximum, and standard deviation of handwriting speed.

In-air time ratio:

The in-air time ratio represents the proportion of time spent by the writer without touching the surface of the tablet. It was found to be a discriminative feature in a recent study interested in the analysis of dysgraphia [312, 313].

Pressure features

	Feature	**t-stat**	**p-value**	**Mean *TD***	**Std. *TD***	**Mean *D***	**Std. *D***
Pressure	Mean Pressure	1.10	0.27	493.25	116.79	676.24	2193.71
	Max Pressure	1.56	0.12	968.27	93.26	1386.66	3540.76
	Std. of Pressure	1.53	0.13	203.84	39.54	283.80	686.99
	Mean Speed of Pressure Change	-9.01	$\mathbf{7.50 \cdot 10^{-17}}$	0.23	0.091	0.015	0.26
	Max Speed of Pressure Change	-2.96	**0.0034**	13.83	3.77	10.69	12.35
	Std. of Speed of Pressure Change	-0.29	0.77	2.50	0.67	2.37	5.79
	Increase of Speed of Pressure Change	2.71	**0.0070**	$-2.41 \cdot 10^{-5}$	$4.89 \cdot 10^{-5}$	$-4.32 \cdot 10^{-6}$	$4.21 \cdot 10^{-5}$
	Nb of Peaks of Speed of Pressure Change	-8.39	$\mathbf{4.63 \cdot 10^{-15}}$	0.0035	$6.9 \cdot 10^{-4}$	0.0026	$6.72 \cdot 10^{-4}$
	Bandwidth of Speed of Pressure Change Freq.	-0.46	0.65	0.0017	$1.93 \cdot 10^{-4}$	0.0017	$2.29 \cdot 10^{-4}$
	Median of Power Spectral of Speed of Pressure Change Freq.	3.20	**0.0016**	0.0022	$1.60 \cdot 10^{-4}$	0.0023	$2.16 \cdot 10^{-4}$
	Dist to Mean of Speed of Pressure Change Freq.	4.87	$\mathbf{2.09 \cdot 10^{-6}}$	$1.72 \cdot 10^{-4}$	$6.26 \cdot 10^{-5}$	$2.31 \cdot 10^{-4}$	$1.15 \cdot 10^{-4}$

Table 3.5: A comparison between the two groups of writers (D dataset and TD dataset) for every feature based on the pressure between the pen and tablet surface. For each feature, we compute the mean and standard deviation of the two groups as well as the t-statistic and p-value for the t-test.

Detailed analysis of all pressure features can be found in Table 3.5.

Pressure: The first features concerning the pressure are simply the mean,maximum, and standard deviation of the pressure.

Speed of pressure change:

To compute the speed of pressure change,we used the same method we used for the speed of handwriting. We worked with averaged buckets of 10 points and divided the time spent by the difference between these two averaged bins of points. The mean, maximum, and standard deviation of these measures can then once again be extracted. The number of peaks of speed of pressure change during handwriting was also extracted. A Gaussian filter was applied to the signal and local minima and maxima of this filtered signal were extracted and normalized by the total amount of handwriting time (excluding the in-airtime).

Speed of pressure change frequencies:

The speed of pressure change can be seen as a time-series, and frequencies can be extracted using a Fourier transform. The same process as that described in Fig.3.2 is followed to extract the Bandwidth of speed of pressure change frequencies, the Median of power spectral of speed of pressure change frequencies, and the Distance to mean of speed of pressure change frequencies.

3.2.4 Tilt features

The Wacom system logged the data measuring the pen tilt with two different angles, which we referred to in this paper as the Tilt-x and Tilt-y angles (see Figure 3.3 for more details). Both angles are measured in the range between$-60°$ and $60°$. The tilt-x reflects the inclination of the pen in the direction of the written line, and the tilt-y reflects the inclination of the pen below the written line.

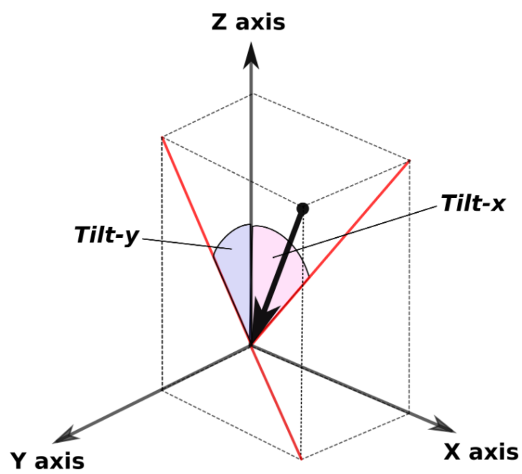

Figure 3.3: The two angles (tilt-x and tilt-y) recorded for the pen. The black arrow represents thepen, and the red segments represent its projection on the XZ and YZ planes, respectively.

Tilt:

Detailed analysis of all tilt features can be found in Table 3.6.

Simple features were extracted for both angles, namely the mean,maximum, and standard deviation of the measurement.

Speed of tilt change:

We computed the speed of tilt-x/tilt-y change in the same way as before, and we extracted the mean, maximum, standard deviation, and number of peaks. Finally, we also computed the evolution of the speed of tilt-x/tilt-y change over time.

	Feature	F statistic	p-value	Mean *TD*	Std. *TD*	Mean *D*	Std. *D*
Tilt	Mean Tilt-x	-1.67	0.096	607.10	53.01	592.90	61.48
	Mean Tilt-y	-0.29	0.77	1233.29	629.65	1204.48	669.94
	Max Tilt-x	2.72	**0.0071**	727.74	75.17	759.64	79.62
	Max Tilt-y	5.73	$\mathbf{3.02 \cdot 10^{-8}}$	1788.75	819.03	2517.14	843.35
	Std. of Tilt-x	3.56	$\mathbf{4.55 \cdot 10^{-4}}$	40.43	14.25	49.00	19.40
	Std. of Tilt-y	0.64	0.52	169.59	269.26	193.70	131.81
	Mean Speed of Tilt-x change	-1.60	0.11	0.024	0.014	0.021	0.012
	Mean Speed of Tilt-y change	-1.15	0.25	0.031	0.15	0.0077	0.043
	Max Speed of Tilt-x change	-1.10	0.27	1.66	0.76	1.54	0.68
	Max Speed of Tilt-x change	1.41	0.16	8.38	18.89	12.74	23.43
	Std. of Speed of Tilt-x change	3.18	**0.0017**	0.18	0.04	0.20	0.037
	Std. of Speed of Tilt-y change	-0.61	0.54	1.04	2.55	0.82	1.16
	Increase of Speed of Tilt-x change	0.29	0.77	$6.32 \cdot 10^{-7}$	$6.16 \cdot 10^{-6}$	$9.17 \cdot 10^{-7}$	$7.03 \cdot 10^{-6}$
	Increase of Speed of Tilt-y change	-0.98	0.33	$9.89 \cdot 10^{-6}$	$9.66 \cdot 10^{-5}$	$-2.83 \cdot 10^{-6}$	$1.36 \cdot 10^{-5}$
	Nb of peaks of Tilt-x Speed	-0.47	0.64	1174.56	235.35	1156.01	307.94
	Nb of peaks of Tilt-y Speed	-1.30	0.19	1093.54	220.77	1045.73	285.59
	Bandwidth of Speed of Tilt-x Change Freq.	9.08	$\mathbf{4.73 \cdot 10^{-17}}$	$3.42 \cdot 10^{-3}$	$2.42 \cdot 10^{-4}$	$3.92 \cdot 10^{-3}$	$5.74 \cdot 10^{-4}$
	Median of Power Spectral of Speed of Tilt-x Change Freq.	1.33	0.19	$3.34 \cdot 10^{-3}$	$2.49 \cdot 10^{-5}$	$3.35 \cdot 10^{-3}$	$6.26 \cdot 10^{-5}$
	Dist to Mean of Speed of Tilt-x Change Freq.	12.56	$\mathbf{6.36 \cdot 10^{-28}}$	$2.27 \cdot 10^{-4}$	$4.35 \cdot 10^{-5}$	$4.34 \cdot 10^{-4}$	$2.04 \cdot 10^{-4}$
	Bandwidth of Speed of Tilt-y Change Freq.	6.19	$\mathbf{2.64 \cdot 10^{-9}}$	$3.45 \cdot 10^{-3}$	$2.72 \cdot 10^{-4}$	$3.72 \cdot 10^{-3}$	$3.36 \cdot 10^{-4}$
	Median of Power Spectral of Speed of Tilt-y Change Freq.	-9.66	$\mathbf{8.93 \cdot 10^{-19}}$	$3.35. \cdot 10^{-3}$	$2.30 \cdot 10^{-5}$	$3.30. \cdot 10^{-3}$	$4.38 \cdot 10^{-5}$
	Dist to Mean of Speed of Tilt-y Change Freq.	7.97	$\mathbf{7.24 \cdot 10^{-14}}$	$2.26 \cdot 10^{-4}$	$2.79 \cdot 10^{-5}$	$2.85 \cdot 10^{-4}$	$8.57 \cdot 10^{-5}$

Table 3.6: A comparison between the two groups of writers (D dataset and TD dataset) for every feature based on the tilt between the pen and tablet surface. For each feature, we report the mean and standard deviation of the two groups as well as the t-statistic and p-value.

Frequency of speed of tilt change:
Using the same method as before,we computed the Bandwidth of speed of tilt change frequencies, the Median of power spectral of speed of tilt change frequencies, and the Distance to mean of speed of tilt change frequencies.

3.3 Results

As described previously, our database is not balanced in terms of positive and negative examples (242 TD children versus 56 D children), which can skew the model towards a larger subpopulation. In order to validate the accuracy, we divided our data into two disjoint sets.

- Training set —70% of TD dataset and 70% of D dataset.
- Testing set —30% of TD dataset and 30% of D dataset.

A k-fold cross-validation [165] (with k=25) on a Random Forest classifier [49] was performed in order to test our model. Due to the differences between positive (dysgraphic children)and negative examples (non-dysgraphic children) in the database,reporting the overall accuracy might be misleading (a model that always predicts non-dysgraphia will be 75% accurate). Following machine learning literature, we report the F1-Score. The F1-Score is the harmonic mean of Precision and Recall. Therefore, the score takes both false positives and false negatives into account, making it more comparable across studies with different proportions of classes. The F1-score is defined as

$$F1 - Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

where

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

and

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}.$$

In our case, the *True Positive* ratio corresponds to the proportion of dysgraphic children correctly labeled dysgraphic, while the *False Negative* ratio refers to the proportion of dysgraphic children incorrectly labeled non-dysgraphic. Finally the *False Positive* ratio defines the proportion of non-dysgraphic children incorrectly labeled dysgraphic.

For our model, after the 25-fold cross-validation, we obtained a F1-score of 97.98% (Std. of 2.68%). We found this result very satisfactory given the small number of dysgraphic recordings used for training the model. We also conjectured that a larger sample would improve the generalizability and robustness of the model.

3.3.1 Robustness of the test

To validate the robustness of the test, we measured how much data per user was needed in order to accurately predict dysgraphia. To that end, we trained the model, using only the first seconds of the test, while keeping the same workflow of training, including the k-fold validation (k=25). In Fig 3.4, we present the F1-score as a function of the length of the portion of the test used to train the model. For example, 15 s means that only the data recorded during the first 15 s of the BHK test were used to train the model. We can see that, after 15 s of testing, the results are already satisfactory (F1-Score of 77.21%), but the high standard deviation (10.34%) may indicate that the model is not generalizable. After 50 s of testing, the F1-Score reaches 93.93%, while the standard deviation drops to 4.6%. For any longer periods of time, the results improve only marginally.

We believe that this result indicates the robustness of our features. Indeed, even with the noise coming with the restricted portion (for example, 15 s) of the test used (a smaller number of examples means less statistical significance), our model still manages to extract relevant information from the features measured. This is an indirect benefit compared to the BHK test, which must be interpreted in its entirety.

3.3.2 Discriminative features

In order to analyze the most discriminative features, we first sort them by importance. Following machine learning literature, we use one of the most popular choices, Gini importance. [49] Table 3.7 presents the eight most important features (i.e., the most discriminative) emerging the Random Forest model (averaged over 25 folds). Features related to frequencies seem to be very discriminative as six out of eight of

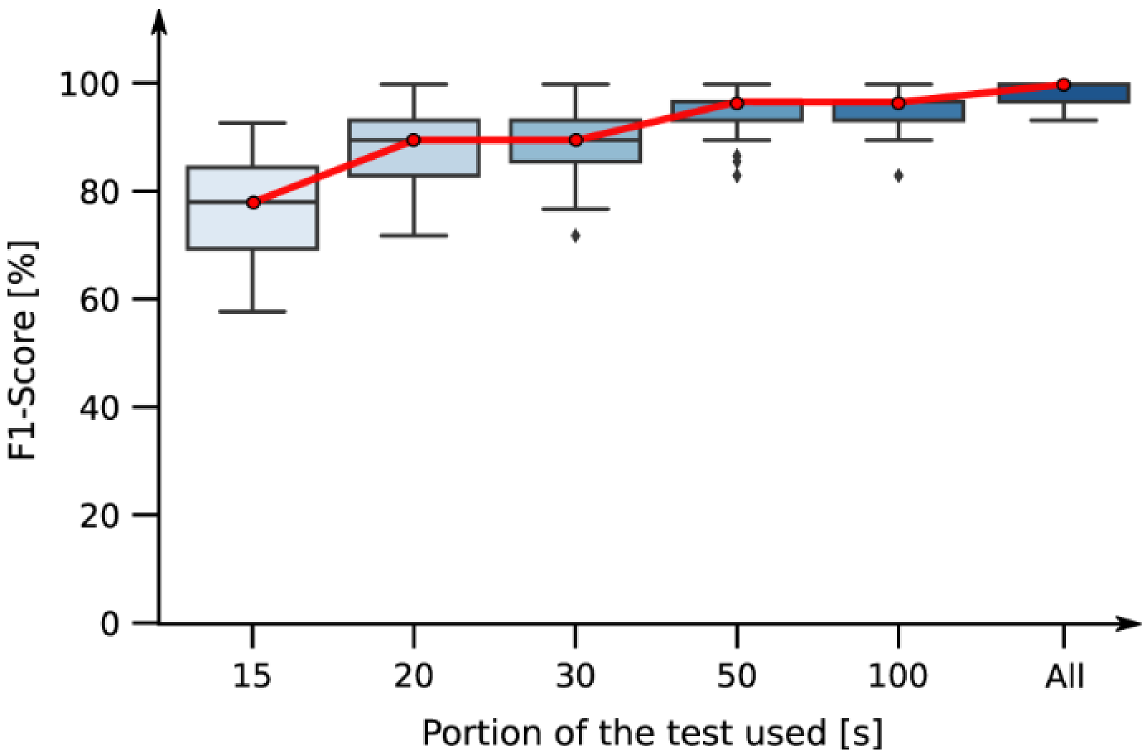

Figure 3.4: Box plot representing the F1-score as a function of time period of the test used for training. We used Random Forest for classification, and each model was trained following the same k-fold, cross-validation procedure with k = 25

the most important features are related to frequencies. Features from all four of our categories are represented among the eight most discriminative features: three are kinematic features, three represent tilt, one is related to pen pressure, and one is a static feature. In the next section, we will analyze these features further

We notice that only one of these features, the space between words, could be extracted if we only had access to the final output of handwriting. This reassures us concerning the value of the digital tablet in assessing handwriting as it provides us access to important information previously inaccessible to clinicians analyzing standard tests, such as the BHK.

3.4 Discussion

3.4.1 Clinical Features Analysis

The most discriminative static feature we found was the Bandwidth of Tremor Frequencies (see left graph of Fig. 3.5). This feature represents the range of tremor frequencies found in the handwriting of the writer under investigation. A high value for this feature means that many tremors were extracted from the handwriting. In Fig. 3.6, we present an example of handwriting from a non-dysgraphic child (on the left) and a dysgraphic child (on the right). The handwriting of the non-dysgraphic child appears to be smooth. Conversely, the handwriting of the dysgraphic writer is not smooth; we can see easily some high-frequency shaking (as in the apostrophe or at the end of the “a”). We hypothesize that this characteristic results in an important value of the Bandwidth of Tremors Frequencies feature. The dysgraphic

Rank	**Category**	**Name**	**Importance (Std.)[%]**
1	Kinematic	Median of Power Spectral of Speed Frequencies	15.71 (9.06)
2	Kinematic	Bandwidth of Speed Frequencies	12.08 (8.00)
3	Pressure	Mean Speed of Pressure Change	9.81 (6.52)
4	Static	Space Between Words	7.45 (6.73)
5	Tilt	Distance to Mean of Speed of Tilt-X Change Frequencies	6.07 (4.30)
6	Kinematic	Distance to Mean of Speed Change Frequencies	5.18 (4.73)
7	Tilt	Bandwidth of Speed of Tilt-X Change Frequencies	4.10 (4.64)
8	Tilt	Median of Power Spectral of Tilt-Y Change Frequencies	2.97 (3.33)

Table 3.7: The most important features found by the Random Forest model, using Gini importance as a metric. We report the ranks, features categories and their importance averaged for the 25 folds and the standard deviation of importance over all folds.

child hesitates more when forming letters, and it is harder for them to control the pen smoothly. This lack of smoothness is indicative of poor motor control, resulting in more noise. Interestingly, this feature is related to the BHK item hesitation and shaking. According to the therapists, a score of 0 (highest score) was obtained by the non-dysgraphic child for this feature, while a score of 3/5 (a low score) was obtained by the dysgraphic child.

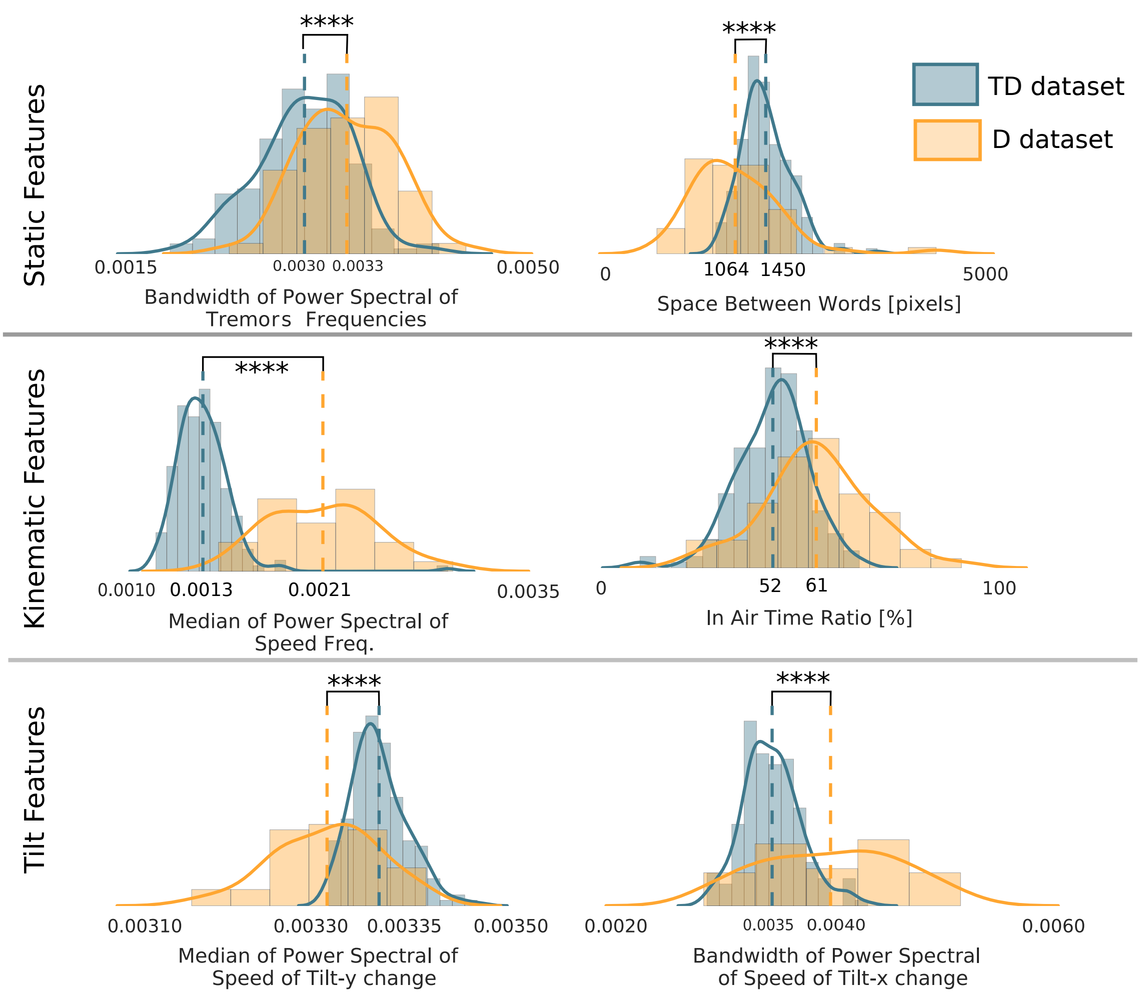

Figure 3.5: Distribution of the dysgraphic children (D dataset) and the non-dysgraphic children (TD dataset). For static features: Bandwidth of Tremors Frequencies and the Space Between Words features. For kinematic features: Median of Power Spectral of Speed Frequencies and the In Air Time Ratio features. For tilt features: Median of Power Spectral of Speed of Tilt-y change and the Bandwidth of Power Spectral of Speed of Tilt-x change features

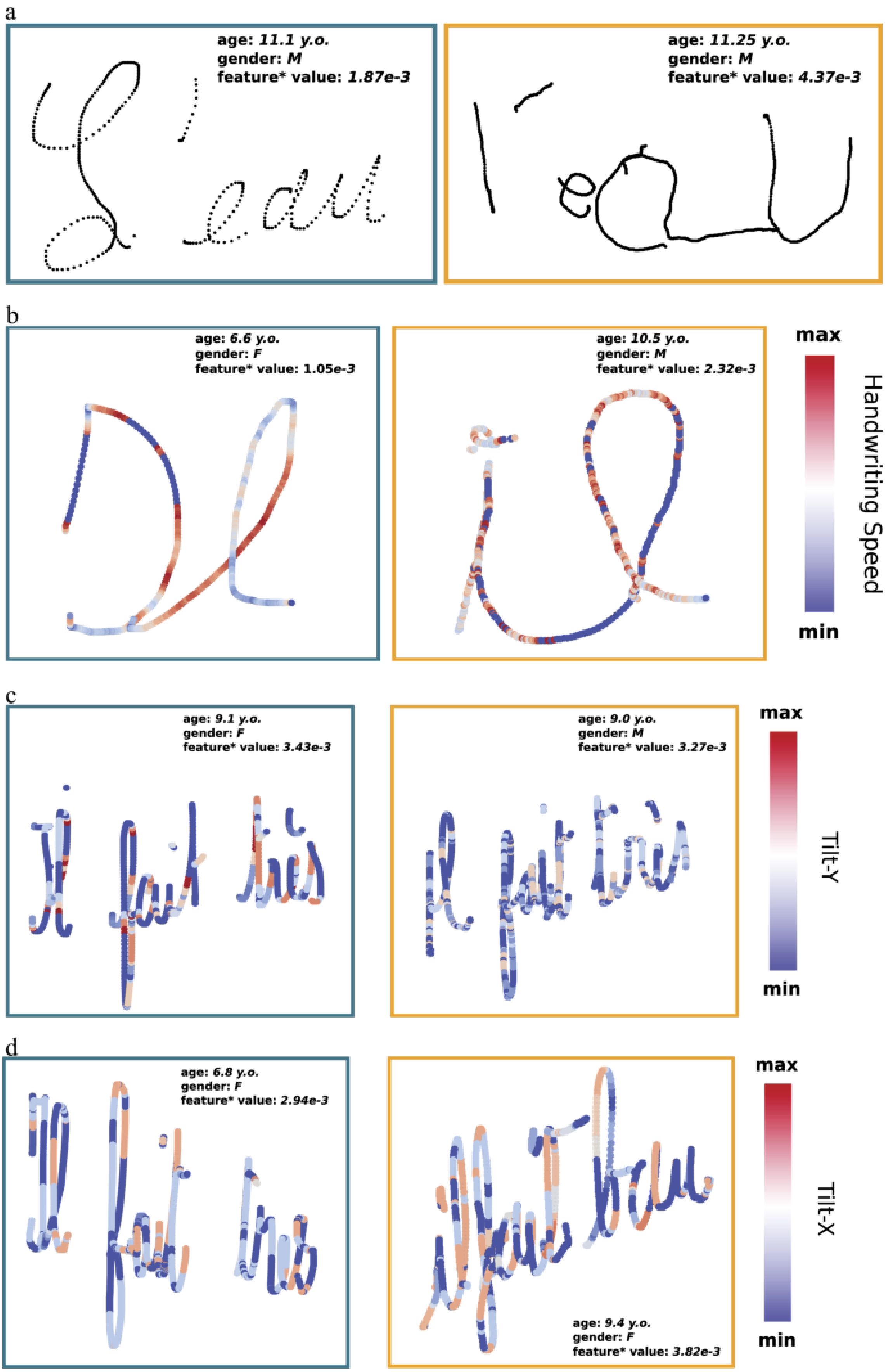

Figure 3.6: A comparison of different metrics for a non-dysgraphic child (left) and a child with dysgraphia (right)

Concerning the Space Between Words feature, we can see in the right graph of Fig. 3.5 that the non-dysgraphic tends to put more space between the words they write. This is related to the BHK item called narrow words. This BHK item indicates pathology if it is not possible to insert the letter "o" between each pair of words, meaning that not enough space is left. Moreover, in the case of dysgraphia, the writing is barely automatized, leading to irregular spaces between words. This irregularity is attested to by the difference in standard deviation that we can observe between the two groups (for more details, see Std. TD and Std. D in Table 3.3).

The most discriminative kinematic feature we found was the Median of the Power Spectral of Speed Frequencies. This feature indicates that the speed frequencies of dysgraphic children are shifted toward high frequencies (see left graph of Fig. 3.5 In Fig. 3.6 b, we present an example of the handwriting of a non-dysgraphic child on the left and a dysgraphic child on the right. The color corresponds to the handwriting speed at the time the points were recorded. In the dysgraphic child's handwriting, we observe very rapid changes in speed (rapid acceleration and deceleration), contrary to what can be found in the handwriting of the non-dysgraphic writer. It is interesting to note that the features linked with acceleration were not found to be discriminative as these sudden changes of speed are local (compensated for by long periods of constant speed). These sudden changes of speed are translated into high frequencies during the Fourier transformation. This feature relates the fact that we can find more saccades during the handwriting of the dysgraphic child due to the lack of automation and control in his/her hand movements. In the case of the BHK test, the only feature related to the kinematics of handwriting is the number of characters written after 5 min. The results of this very basic feature show that the dysgraphic children are slower than the non-dysgraphic ones.

Another interesting feature that was found to be discriminative was the in-air time (the proportion of time spent with the pen not touching the surface of the tablet), as can be seen in the right graph of Fig. 3.5. This result appears to be in line with previous findings. [313].

As can be seen in Fig.3.5, the frequencies extracted from the speed of tilt change are very discriminative of dysgraphia. Concerning the Tilt-y, in contrast to what was observed for other categories of features, we can see that the non-dysgraphic children seem to exhibit higher frequencies during their handwriting. This finding is highlighted in Fig. 3.6c. For every point recorded, the color of the trace represents the speed of the tilt-y change. We can see that the dysgraphic child stays very constant, maintaining the tilt-y of his/her pen (almost no variations in the speed of the tilt-y change, with small absolute value). The non-dysgraphic child, in contrast, presents very rapid variations in his/her tilt-y change speed (rapid acceleration and deceleration). These very sudden variations are translated into high frequencies in the Fourier domain, shifting the median of the power spectral to high frequencies. Thus, we can infer that the non-dysgraphic child is able to change very frequently and quickly the tilt of his/her pen in the y-axis, whereas the dysgraphic child displays less tilt-y variation abilities, probably due to a more constraining and rigid pen grip.

Concerning the tilt-x, although the distribution of dysgraphic children is very spread out (see the right graph of Fig. 3.5), the dysgraphic children seem to present a larger range of frequencies in their handwriting concerning the speed of tilt-x change than seen typically in developing children. This means that they are not constant in the way they move their pen in the ZX plane (see Figure 3.3 for more details). This finding is highlighted in Fig. 3.6. For every point recorded, the color of the trace represents the speed of the tilt-x change. We can see more variations in the speed of tilt-x change for the dysgraphic child compared to that of the non-dysgraphic child, who seems to present more control in his/her movement. Contrary to the pen tilt in the direction perpendicular to the handwriting global direction (perpendicular to the lines of the paper sheet), proficient writers exhibit less variations (more control) in the speed of tilt change (and also the tilt, itself) in the direction of the lines of the paper sheet. Correlation between features

We analyzed correlations between pairs of 53 features extracted throughout this study. We found a strong, positive correlation between the median of the power spectral of speed frequencies and the bandwidth of speed frequencies (Pearson's test: $r = 0.96$, $p < 0.001$), as well as between the median and the distance to mean speed change frequencies (Pearson's test: $r = 0.65$, $p < 0.001$). In other words, these three features describe the same "abnormal" high-speed frequencies in the handwriting: the more a child's frequencies differ from the average, the more these frequencies will be shifted towards high frequencies.

This finding encouraged us to test a simpler model, using only the median of the power spectral of speed frequencies. Despite the high correlation between the median and the bandwidth, adding the additional feature still has additional predictive power, as indicated by our cross-validation process. In particular, the model with both features presents a F1 score of 0.98 (Std. = 0.03), while the simplified model has an F1 score of 0.95 (Std. = 0.05). We conjecture that two correlated features, despite being linearly correlated, are still discriminative in a non-linear manner. Thanks to the robustness of the Random Forest in terms of correlations and non-linear structures, we obtained better results. We decided to report on the more accurate model, leaving the decision to decrease model complexity to the user.

3.4.2 Main findings

We designed a method allowing clinical assessment of dysgraphia using a consumer tablet. Compared to existing tools, our method is cheaper, faster, free of human bias, validated on clinical data, and is applicable to Latin alphabet. The method leverages information contained not only in static writing but also in its dynamics. These characteristics make it useful not only as a clinical diagnostic tool, but also as a tool for parents or guardians to obtain high-quality assessment more frequently throughout development of the child. Granularity of the features allows to obtain more specific diagnosis and can lead to design of new exercises tailored to specific motor-impairments. In this section, we discuss accuracy, clinical relevance, applicability, and potential impact of our work.

On average, 96.6% (standard deviation of 5.02%) of the writers with dysgraphia were diagnosed correctly, while we achieved a 0.78% (standard deviation of 1.82%) false positive rate. The final model reached an F1-Score of 97.98% (standard deviation of 2.68%) Note that the inter-rater correlation in BHK is 0.89. Since our algorithm outperforms this value, we conclude that the algorithm learned to mimic the rater. These findings suggest that adding data from other raters should not only reduce bias, but also allow us to surpass the accuracy of each individual rater.

Our diagnostic system has the advantage of being almost costless (not including the cost of the tablet) and very fast (only a few milliseconds to deliver the diagnosis compared to 10 min for the BHK test). It also reduces subjectivity as the model is permeable to all the external parameters that can bias a human. Moreover, it is interesting to see that, among the 53 features used by our model, most of them are very technical and "low level", i.e., measuring the mechanics of writing. In that way, our test is more robust to differences in handwriting style, language, and understanding of the text by the subject. Indeed, these features (for example, the three most discriminative features: the Median of Power Spectral of speed frequencies, the Bandwidth of Speed Frequencies and the Mean Speed of Pressure Change) can be interpreted the same way independently of the language or handwriting direction. For example, languages written from right to left, such as Hebrew, or from left to write, such as French, still share the same low-level characteristics. In future work, we envision testing the method for its robustness with other tests and, especially, other languages. Whenever the retraining of the model is needed, we are interested in validating it if an overlap between the most predictive features is large.

As the model includes 53 criteria of a child's handwriting, the system helps us to build a more precise profile of the child compared to standard tests, in which only a few different criteria are available. Moreover, our model has the consequent advantage of not being restricted to the use of static features, such as in the current standard tests, but also uses kinematics, pressure, and tilt features. In the BHK test, the 13 items reflect what is wrong in the final product of the child's handwriting, but do not give indications on why it is wrong. We believe that our system explores the handwriting pathology at a deeper level, and it permits analyzing the handwriting characteristics that lead to the imperfections seen in the final product. This brings with it potential therapeutic value, especially for remediation. Given new features, it is now possible to reach a more specific diagnosis rather than the general binary indication of dysgraphia. This will help clinicians focus on specific remediation exercises (e.g., exercises to increase the stability of the pen tilt or the change in pressure necessary for handwriting automation).

3.5 Conclusion

We demonstrated, using handwriting's static, dynamic, pressure, and tilt features extracted from a digital tablet, that we could diagnose dysgraphia very accurately. We believe that the knowledge gained from the analysis of the features extracted during this study can be applied to designing a new test to diagnose dysgraphia. This modernized test has the advantage to also assess the dynamic of handwriting, and the pressure of the pen as well as its tilt. In the future, we hope to design a new test with words maximizing the feature differences between dysgraphic and non-dysgraphic children.

Electronic tablets that are not expensive and easily interpretable algorithms such as random forest algorithms, can allow us to extract relevant handwriting features. These allow to classify properly and eventually with a better reproductibility writing disorders. However, the same input needs to be interpreted differently depending on the age. The same writing sample can be normal for a child of 6, and pathological for a child of 10 since it is expected that, with age and training, the motor performances become better. We should be able to describe the normal development and to show which kind of digital features are the most important, depending on the age, to discriminate the children who need a diagnosis and ultimately a treatment and those who don't. Finally, reducing the clinical heterogeneity, thanks to the creation of subroups (i.e., clusters), would allow to study the specific evolution, impairment and effect of treatment in more homogeneous subgroups.

Chapter 4

A new classification of dysgraphia

Parts of this chapter are published in Plos One journal, under the title "Acquisition of handwriting in children with and without dysgraphia: A computational approach", Gargot, T., Asselborn, T., Pellerin, H., Zammouri, I., M. Anzalone, S., Casteran, L., ... Jolly, C. (2020). PloS one, 15(9), e0237575.

Abstract

Introduction

Handwriting is a complex skill to acquire and it requires years of training to be mastered. Children presenting dysgraphia exhibit difficulties automatizing their handwriting. This can bring anxiety and can negatively impact education.

Materials and methods

280 children were recruited in schools and specialized clinics to perform the Concise Evaluation Scale for Children's Handwriting (BHK) on digital tablets. Within this dataset, we identified children with dysgraphia. Twelve digital features describing handwriting through different aspects (static, kinematic, pressure and tilt) were extracted and used to create linear models to investigate handwriting acquisition throughout education. K-means clustering was performed to define a new classification of dysgraphia.

Results

Linear models show that three features only (two kinematic and one static) showed a significant association to predict change of handwriting quality in control children. Most kinematic and statics features interacted with age. Results suggest that children with dysgraphia do not simply differ from ones without dysgraphia by quantitative differences on the BHK scale but present a different development in terms of static, kinematic, pressure and tilt features. The K-means clustering yielded 3 clusters (Ci). Children in C1 presented mild dysgraphia usually not detected in schools whereas children in C2 and C3 exhibited severe dysgraphia. Notably, C2 contained individuals displaying abnormalities in term of kinematics and pressure whilst C3 regrouped children showing mainly tilt problems.

Discussion

The current results open new opportunities for automatic detection of children with dysgraphia in classroom. We also believe that the training of pressure and tilt may open new therapeutic opportunities through serious games.

4.1 Introduction

Despite the inherent progressive learning of writing, so far no study using digital features took into account age and had a developmental approach. We still do not know how the selected features classifying children with dysgraphia evolved in TD children. In addition, we don't know whether their ability to detect children with dysgraphia changed with age.

In the current study, we aimed to extend our work [20] addressing the effect of age, and the heterogeneity of dysgraphia. Our objectives were the following:

1. First, we aimed to present the learning and acquisition of handwriting from a developmental approach (according to child age). We explored TD children in order to better understand typical development (TD dataset only) and children with dysgraphia (D dataset)

2. Second, we aimed to identify the best features, to diagnose children with dysgraphia (according to age) both using the clinical gold standard method as well as relevant digital features [20].

3. Third, we performed unsupervised clustering of children with dysgraphia by applying a K means clustering of discriminative digital features, to assess how many clusters of patients had a similar profile and to identify their main characteristics.

4.2 Materials and methods

4.2.1 Participants

The present study was conducted in accordance with the Declaration of Helsinki and was approved by the Grenoble University Ethics Committee (agreement no. 2016-01-05-79). It was conducted with the understanding and informed written consent of each child's parents and the oral consent of each child. In total, we recruited 280 children. Two hundred thirty-one children were recruited at different schools from Grenoble area. The exclusion criteria were: having a known specific disability or characterized disorder like any neurodevelopmental disorder and being a non-French native. In this study no specific neurological and cognitive assessments were conducted. The absence of disorders was assumed using the teachers' judgments of children's academic achievement. Forty-nine children were recruited on the basis of a clinical diagnosis of dysgraphia from the Reference Center for Language and Learning Disorders at Grenoble University Hospital, a specialized clinic for learning impairments. Since the diagnosis of dysgraphia is not recommended during the 1^{st} grade the children with dysgraphia from this specialized center were excluded. The diagnosis of children from the specialized clinics are reported in Table 4.1.

4.2.2 Procedure

The BHK test consists of copying a text beginning with simple monosyllabic words and evolving towards more complex words for five minutes onto a blank paper.

Table 4.1: **Diagnosis of children in the specialized clinic**

Isolated disorder: n=26 (55,3%)	n=
DCD	5
DL	9
ADHD	7
dyscalc	3
dysph	2
2 comorbiditiess: n=15 (31,9%)	
DCD/DL	1
DCD/ADHD	2
DCD/dysph	2
DL/ADHD	4
DL/dyscalc	1
DL/dysph	2
ADHD/dysph	2
dyscalc/dysph	1
3 comorbidities: n=5 (10,7%)	
DCD/DL/ADHD	2
DCD/ADHD/dyscalc	1
DL/ADHD/dysph	1
DCD/DL/executive disorder	1
4 comorbidities: n=1 (2,1%)	
DCD/DL/ADHD/dysph	1

DCD: developmental coordination disorder, DL: dyslexia, ADHD: Attention Deficit Hyperactivity Disorder, dyscalc: dyscalculia, dysph: dysphasia

Different features reflecting handwriting quality (e.g., letter form, size, alignment, spacing...) are scored to generate a final handwriting quality score. The final quality score is a degradation score. Higher scores correspond to more errors and a worse quality. A speed score is also provided (i.e., the number of characters written in five minutes) (see BHK scores Table 4.2).

The 298 children involved in this study performed the BHK test by writing on a sheet of paper affixed to a Wacom graphic tablet (sampling frequency = 200Hz; spatial resolution = 0.25mm). A Wacom Intuos 4 tablet was used for the children recruited in schools, while a Wacom Intuos 3 tablet was used for the children recruited in the specialized clinic. Pressure data were carefully calibrated between the two tablets. The weights X were carefully chosen (from 0g (pen only) to 400g) in order to explore all range of tablet outputs until saturation. The relation between the weight in input (X) and the value returned by the tablet (Y) could be extracted and was found to be very similar for the two tablets (Spearman correlation > 0.99, $p < 0.001$, mean square error = 0.6). A 4th degree polynomial fit was created to model the function describing the X/Y relation of the first tablet and used on the second to correct the output. After this correction, the spearman correlation was found to be 0.99998 ($p << 0.001$) and the mean squared error was 5.1 x 10-3.

Two junior psychomotor therapists were trained by the same senior psychomotor therapist to score BHK. Then, the 2 juniors therapists annotated independently all BHK both for quality and speed scores. For the 30 least consistent scores (BHK score > 5), the senior therapist scored the BHK.

These professionals were blinded to the demographics and clinical characteristics of the children. Scoring included two dimensions: (1) handwriting velocity assessed through the number of characters written in five minutes and (2) handwriting quality on the five first sentences of the text according to 13 items using a semiquantitative method (BHK quality scores: Table 4.2). We calculated the final inter rater-reliability using intra-class correlation, ICC = 0.97 (95% CI: 0.96-0.98). Finally, according to the normal scores by age measured during the previous validation of the scale [72], we computed a qualitative score (quality of the writing) and a quantitative score (speed of the writing).

In a previous work [20], 53 digital handwriting features were defined and used to

Table 4.2: **Clinical-Gold Standard (BHK scores) and digital features on handwriting.**

BHK scores	BHK quality score based on the sum of 13 quality item scores (raw and normalized with age)	Writing is too large
		Widening of left-hand margin
		Bad letter or word alignment
		Insufficient word spacing
		Chaotic writing
		Absence of joins
		Collision of letters
		Inconsistent letter size (of x-height letters)
		Incorrect relative height of the various kinds of letters
		Letter distortion
		Ambiguous letter forms
		Correction of letter forms
		Unsteady writing trace
	BHK speed (raw and normalized with age)	The numbers of characters written in 5 min
Digital features	Static features	Space between Words
		Standard deviation of handwriting density
		Median of Power Spectral of Tremor Frequencies
	Kinematics features	Median of Power Spectral of Speed Frequencies
		Distance to Mean of Speed Frequencies
		In-Air-Time ratio
	Pressure features	Mean Pressure
		Mean speed of pressure change
		Standard deviation of speed of pressure change
	Tilt features	Distance to Mean of Tilt-x Frequencies
		bandwidth_tiltx
		Median of Power Spectral of Tilt-y Frequencies

BHK quality scores have each a score between 0 and 5 according to (1) their age for size of writing and widening of left-hand margin and (2) a score of 0 or 1 for each line of the 1st paragraph for other quality items.

train a random forest classifier to diagnose dysgraphia. In this work, we only used the features that were found to be the most important in the aforementioned random forest model according to the Gini importance metric [20]. This means that all the features were significantly different between TD and D based on a binary diagnostic classification (BHK threshold). As expected, all digital features were significantly associated with continuous BHK quality score when the models were applied on TD children and children with dysgraphia. To maintain a good balance and to compare the different groups of features, we selected the three most important features for each of the following four groups that we distinguished: static, pressure, kinematic, and tilt. In the following paragraphs, we briefly provide their respective definitions (Table 4.2).

Static features

They are purely geometric characteristics of the written text. Among static features, we selected: (1) Space Between Words, which refers to the distance between words averaged for the entire text; (2) SD of handwriting density, where a grid with 300-pixel cells covering the entire range of the handwriting trace is created. The number of points recorded by the Wacom tablet in each cell, if present, was stored in an array. The SD of this array is represented by this feature. Also, (3) Median of Power Spectral of Tremor Frequencies was included. Here, the tremors present in the handwriting of children can be calculated for a given packet of points and can thus be described as a series. By doing so, we can apply the usual time series analysis and, in particular, the Fourier transform and take the median of the spectral distribution resulting from it. What we can observe from this is that children having handwriting difficulties show abnormal movements that translate in high frequencies in the Fourier transform, resulting in a shift of the median towards higher frequencies.

Kinematic features

They regroup features describing the dynamic of the handwriting process. Among these features, we selected: (1) Median of Power Spectral of Speed Frequencies. We can interpret handwriting as a two-dimensional time series. In the same way as for the Median of Power Spectral of Tremors Frequencies, a Fourier transform can be calculated as well as the median of the spectral distribution resulting from it. We can observe very fast changes of speed in the handwriting of children with dysgraphia. These abnormal changes of speed are translated in high frequencies in the Fourier transform resulting in a shift of the median towards higher frequencies. (2) Distance to Mean of Speed Frequencies: This feature refers to the distance between the spectral distribution of the writing of the child under investigation and the writing of the typical child of the same age. The higher this distance is, the more eclectic the handwriting of this particular writer is. (3) In-Air-Time ratio: represents the proportion of time spent by the writer without touching the surface of the tablet.

Pressure features

They regroup features using the notion of pressure measured between the pen tip and the tablet surface. Among these features, we selected: (1) Mean Pressure, which is simply the average of all record points of pressure during the test's duration and (2) Mean Speed of Pressure Change, which was extracted by working with averaged buckets of 10 record points of pressure and dividing the time spent by the difference between these two averaged bins of points. This feature is then computed by taking the mean of all measurements. Also, (3) SD of Speed of Pressure Change was selected. This feature is computed in the same way as the feature above: although, instead of applying the mean function, we applied the SD to compute it.

Tilt features

They regroup features using the notion of tilt between the pen and the surface of the tablet. Among these tilt features, we selected: (1) Distance to Mean of Tilt-x Frequencies: This feature refers to the distance between the spectral distribution of the writing of the child under investigation and the one from a typical child of the same age. The higher this distance is, the more eclectic the handwriting of this particular writer. Also, we selected (2) The Bandwidth of Speed of Tilt-x Frequencies: In the same way as described above, the Fourier transform of the two-dimensional time series can be calculated with the tilt-x logs as well as the bandwidth of the spectral distribution resulting from it. For the tilt-x, we can observe that children having handwriting difficulties present spreader tilt-x frequencies and thus a larger bandwidth. Lastly, we included (3) Median of Power Spectral of Tilt-y Frequencies. Here, the Fourier transform of the two-dimensional time series can be calculated with the tilt-y logs as well as the median of the spectral distribution resulting from it. For the tilt-y, we can observe that children having handwriting difficulties present lower tilt-y frequencies and thus a lower median.

Statistical models

Since we selected the 12 digital features through machine learning classifying BHK scores as threshold (binary classification), we considered inappropriate to use direct group comparisons (TD vs. D). To take into account the effect of age, and possible interactions between a given digital feature and age, we applied linear regressions considering each feature as a continuous variable to explain the BHK as a continuous variable without consideration of the diagnosis threshold. To do so, each of the 12 digital features was normalized in order to assess their effect in linear regression models.

To understand how a given digital feature is explaining or not BHK quality taking into account grade and gender, a linear regression model per feature was created to predict the continuous BHK quality score. This model was adjusted for grade and gender. In the same way, a model was created to predict the BHK speed score. The formulas can be described as follows:

$$BHKScore \sim Normalized(feature) + grade + gender + \varepsilon$$

To understand how a given digital feature explaining continuous BHK changes according to a child's grade, a similar model with interaction [grade*Normalized(feature)] was also created. In other words, the model can show the relative importance of a given digital feature to diagnose dysgraphia according to age. As recommended in the BHK manual, we selected the grade rather than the age to assess the effect on education, since the writing process is learned at school and not spontaneously. The formulas can be described as follows:

$$\begin{aligned} BHKScore \sim Normalized(feature) + grade + gender + \\ + grade * Normalized(feature) + \varepsilon \end{aligned} \tag{4.1}$$

Since the distribution of the residuals was not normally distributed, a bootstrap analysis (with 10,000 replications) was performed to assess the 95% confidence intervals (95%CI) and p values. These were respectively obtained by BCA (bias-corrected and accelerated) bootstrap and percentile bootstrap with the R boot package. As said previously, we performed these analyses on the TD dataset only to explore how digital features predict writing (BHK) quality and speed in TD children, then on the TD + D dataset to explore how digital features predict writing (BHK) quality and speed in a mixed population that resembles a more realistic situation in the context of school detection of D children .

Clustering

Finally, we tested the theoretical classification of Deuel [103] by a K-means clustering of our digital features, to assess how many clusters of patients had a similar profile and to identify their main characteristics. We used the elbow method to explore the best numbers of clusters.

4.3 Results

4.3.1 Participant's demographics

Our first aim was to better characterize the children recruited from schools and to assess whether or not few had dysgraphia. After clinical assessment of BHK tests of the 280 children from our dataset, we confirmed dysgraphia in all children recruited in the special clinics and detected 13 (5.63%) children with dysgraphia among those recruited from regular schools. Speed dysgraphia (slow writing) was observed in 12 children, with all of them showing also qualitative dysgraphia (poor quality, legibility). Thus, we defined the diagnostic category of dysgraphia based on the BHK quality score only. Therefore, after re-annotation of all BHKs, our dataset was composed of 218 children in the control group, without dysgraphia called the TD group, and 62 children in the experimental group, with dysgraphia called the D group (see Fig. 4.1).

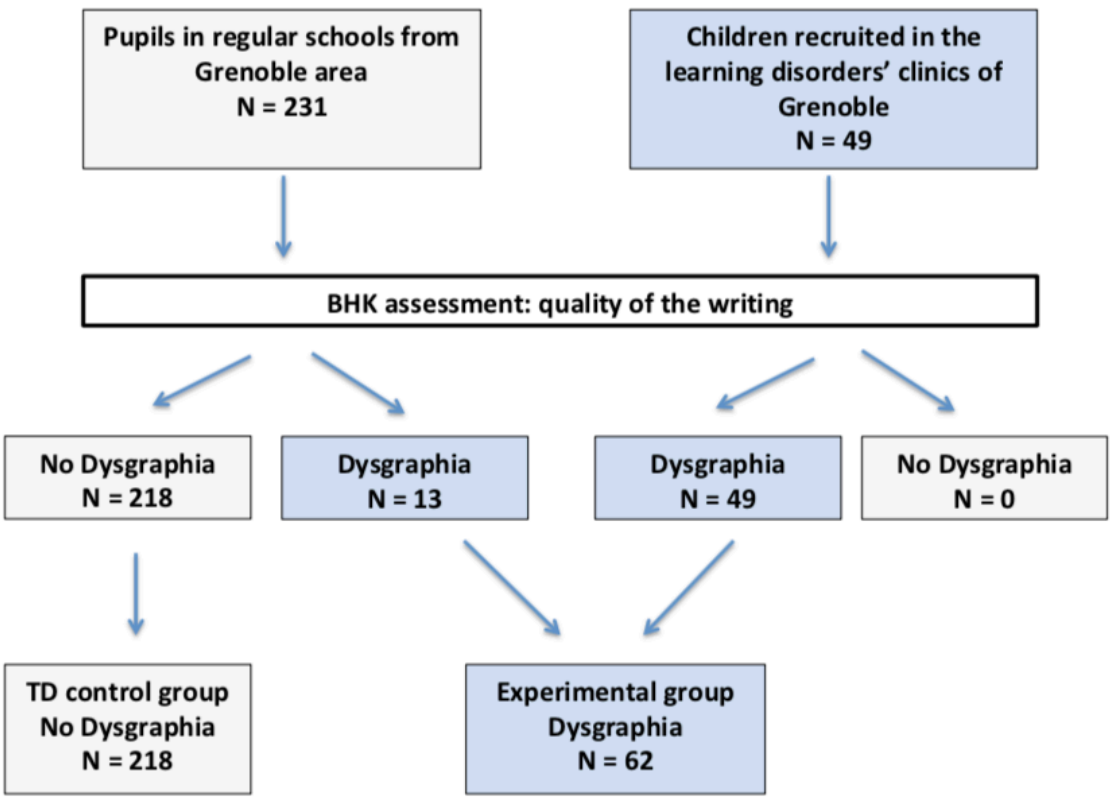

Figure 4.1: **Annotation of the database with the BHK test defining children with dysgraphia (writing quality too bad, BHK quality score too high) and children without dysgraphia**

Table 4.3 summarizes the main characteristics of the two groups. The TD and D children had similar ages of around nine years on average despite a tendency of older age in the group with dysgraphia. Most children were right-handed. There was a gender bias (girls were underrepresented in the D group).

Table 4.3: **Descriptive statistics of the participants (TD and D)**

	TD group (No dysgraphia) (n=218)	**D group (Dysgraphia)** (n=62)	**p-value**
Age: mean (SD)	8.7 (1.53)	9.13 (1.2)	0.056
Males/Females	108/110	44/18	**0.003**
Right-handed / Left-handed	190/28	57/5	0.30
BHK quality score: mean (SD)	14.41 (5.16)	27.09 (6.83)	**0.001**
Grade 1: mean (SD)	n=48; 20.07 (5.39)	n=1; 35.5	0.10
Grade 2: mean (SD)	n=42; 13.17 (4.56)	n=16;33.35 (6.22)	<**0.001**
Grade 3: mean (SD)	n=36; 13.6 (3.66)	n=15; 26.99 (5.76)	<**0.001**
Grade 4: mean (SD)	n=44; 12.68 (3.4)	n=20; 24.1 (4.75)	<**0.001**
Grade 5: mean (SD)	n=48; 12.02 (3.45)	n=10; 22.37 (5.51)	<**0.001**
BHK speed scores: mean (SD)	195.9 (94.6)	139.5 (86.6)	<**0.001**
Grade 1: mean (SD)	n= 48; 74.83 (18.32)	n=1; 61,5	0.52
Grade 2: mean (SD)	n=42; 152.29 (43.27)	n=16; 70.4 (23.53)	<**0.001**
Grade 3: mean (SD)	n=36; 184.97 (42.43)	n=15; 123.67 (47.36)	<**0.001**
Grade 4: mean (SD)	n=44; 262.27 (56.99)	n=20; 160.78 (81.62)	<**0.001**
Grade 5: mean (SD)	n=48; 302.54 (50.42)	n=10; 239.28 (103.53)	**0.03**

Non parametric (Wicoxon rank sum) tests were performed to compare BHK quality score for the 2 whole datasets and for each grade, (SD for standard deviation, TD for Typically Developing, D for dysgraphia)

4.3.2 Handwriting acquisition

Handwriting explained from the BHK features

Fig. 4.2 summarizes the handwriting quality and speed BHK scores for both the TD and D datasets. As expected, we could see an improvement of the handwriting quality (decrease of the BHK quality score) together with an increase of the writing speed with the age of children. By definition, children with dysgraphia had a lower quality versus TD children. Normalized score allow comparisons between grades. The cut-off for a diagnostic of qualitative and quantitative (legibility and speed) dysgraphia is -2.

Handwriting explained from the digital features

Twelve digital features expressing handwriting on different aspects (static, kinematics, pressure, and tilt) were selected from the work of Asselborn et al. [20]. In Fig. 4.3, the link between the digital features and the BHK raw quality score in terms of function of the grade is presented (children without dysgraphia, TD dataset).

Since we selected these features on the basis of their importance on the simple binary classification between children with or without dysgraphia, we wanted to assess whether they were also able to explain the continuous BHK quality score (inverse of the handwriting writing quality) of both the D dataset and TD datasets. For this purpose, multivariate linear regression models were used to compute the correlation between the 12 digital features and the BHK scores (quality or speed).

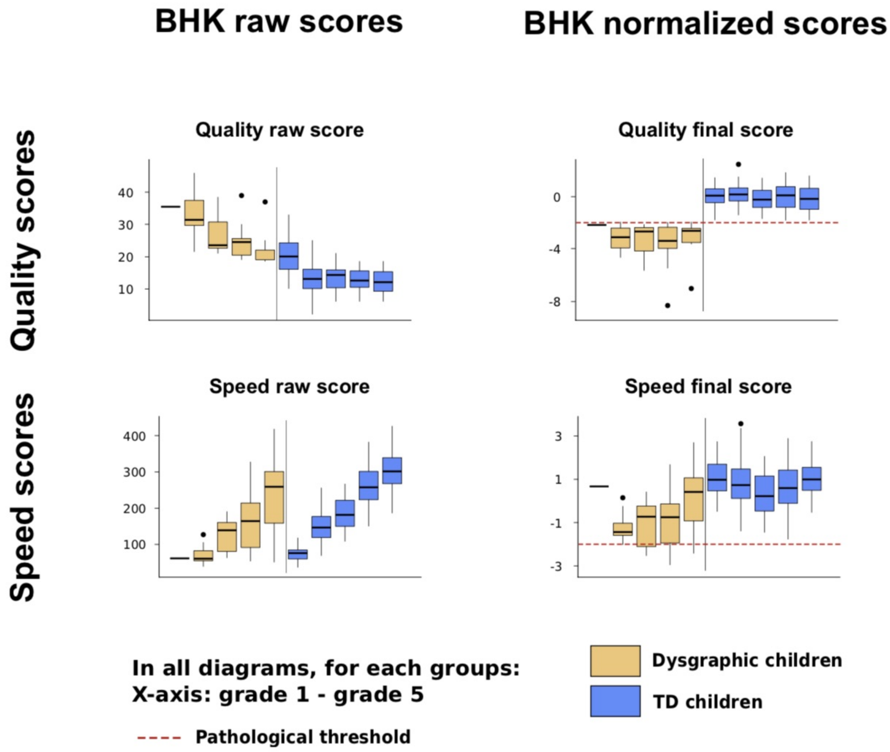

Figure 4.2: **BHK quality and speed scores according to grade in children with typical development and in children with dysgraphia**
Raw score (left) and normalized score (right). Notice that the BHK quality score is a degradation score. The higher the score is, the more the handwriting is impaired. The speed raw score is the number of letters written during 5 minutes.

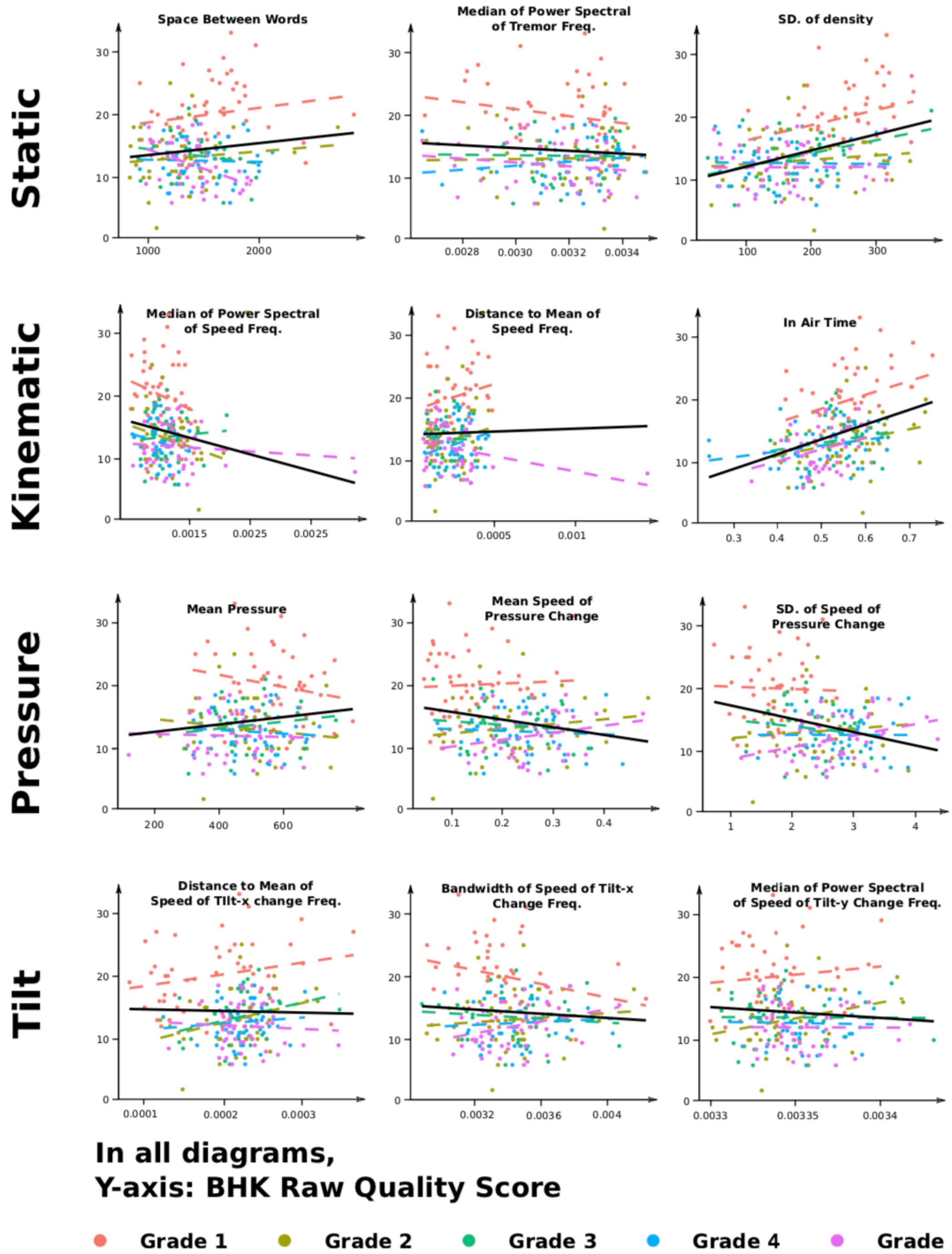

Figure 4.3: **The impact of the 12 digital features on the BHK raw quality score (opposite of handwriting quality) for children without dysgraphia (TD dataset) and for all grades.**

Table 4.4: **Multivariate models to predict the BHK quality raw score**

Category	Feature	Dataset	Feature estimate	CI95% low	CI95% up	p value
Static	Space Between Words	TD	0.45	-0.11	1.05	0.116
		TD + D	-1.16	-2.15	0.008	**0.033**
	SD of Handwriting Density	TD	0.98	0.34	1.67	**0.004**
		TD + D	2.09	1.03	3.04	**<0.001**
	Median of Power Spectral of Tremor Freq.	TD	-0.25	-0.8	0.31	0.374
		TD + D	1.39	0.68	2.19	**0.001**
Kinematic	Median of Power Spectral of Speed Freq.	TD	-0.48	-1.13	-0.03	**0.038**
		TD + D	3.65	2.68	4.49	**<0.001**
	Distance to mean of Speed Freq.	TD	0.17	-0.29	0.9	0.479
		TD + D	2.42	1.43	3.45	**<0.001**
	In Air Time Ratio	TD	0.85	0.23	1.52	**0.006**
		TD + D	2.44	1.36	3.41	**<0.001**
Pressure	Mean Pressure	TD	-0.03	-0.65	0.57	0.935
		TD + D	-1.25	-2.07	-0.3	**0.008**
	Mean Speed of Pressure Change	TD	0.09	-0.58	0.84	0.793
		TD + D	-2.56	-3.51	-1.61	**<0.001**
	SD of speed of Pressure Change	TD	-0.12	-0.9	0.61	0.769
		TD + D	-2.32	-3.3	-1.4	**<0.001**
Tilt	Distance to Mean of Tilt-x Freq.	TD	0.42	-0.21	1.03	0.178
		TD + D	3.35	2.54	4.1	**<0.001**
	Bandwidth of Power Spectral of Tilt-x Freq.	TD	-0.22	-0.78	0.31	0.435
		TD + D	2.2	1.17	3.06	**<0.001**
	Median of Power Spectral of Tilt-y Freq.	TD	0.16	-0.45	0.76	0.597
		TD + D	-2.46	-3.27	-1.65	**<0.001**

The higher the score, the lower the handwriting quality, for typically developing children only (TD dataset), and all children together (TD + D dataset).

Quality association Table 4.4 shows the association between the digital features and the raw BHK quality score (opposite of handwriting quality) for the children without dysgraphia only (TD dataset) as well as for all children taken altogether (D and TD datasets). As expected, since all these features already classified in a proper manner dysgraphia on a simple binary classification in Asselborn et al. [20], all digital features were also significantly associated with continuous BHK quality score when the models were applied on TD children and children with dysgraphia. However, only three digital features (out of 12) were significantly associated with the BHK quality score of TD children.

This finding is interesting, as it shows that the digital features seem to belong to two groups: all of them are useful to explain the difference of handwriting quality between TD children and children with dysgraphia, but only a few features are useful for predicting the handwriting quality of TD children without dysgraphia. In other words, it means that some features become interesting to predict the quality score only when the score is above a certain threshold (i.e., the score only reached by children with dysgraphia as can be seen in Fig. 4.2). These features are the ones able to explain the quality difference between children with dysgraphia and TD children.

As there are several potential causes of dysgraphia with different severities, the variability of handwriting is larger in the D dataset versus the TD dataset. In view of the limited size of our D dataset, the interpretation of the digital feature acquisition of the children with dysgraphia may be difficult. For this reason, we decided to focus our feature interpretation on the children without dysgraphia.

Among the three features able to explain the BHK quality score of children without dysgraphia only, we found two kinematic features (Median Power Spectral Speed Frequencies and In Air Time, respectively) and one static feature (Standard Deviation (SD) of Handwriting Density). As can be seen in Table 4.4 and in Fig. 4.3, the In Air Time Ratio as well as the SD of Handwriting Density are positively correlated with the BHK quality score. This means that a reduction of the In Air

Table 4.5: **Multivariate models to predict the BHK speed raw score for typically developing children (TD dataset), and all children together (TD + D dataset).**

Category	Feature	Dataset	Feature estimate	CI95% low	CI95% up	p value
Static	Space Between Words	TD	5.55	0.01	11.46	0.057
		TD + D	16.6	5.64	25.1	**<0.001**
	SD of Handwriting Density	TD	-16.89	-23.5	-9.53	**<0.001**
		TD + D	-21.18	-29.19	-12.56	**<0.001**
	Median of Power Spectral of Tremor Freq.	TD	0.62	-4.76	6.05	0.831
		TD + D	-12.14	-18.47	-6.28	**<0.001**
Kinematic	Median of Power Spectral of Speed Freq.	TD	-6.24	-12.94	-1.32	**0.013**
		TD + D	-31.37	-38.65	-24.26	**<0.001**
	Distance to mean of Speed Freq.	TD	4.15	-1.39	12.1	0.09
		TD + D	-19.82	-27.34	-13.34	**<0.001**
	In Air Time Ratio	TD	-21.37	-27.6	-14.85	**<0.001**
		TD + D	-27.71	-35.66	-19.62	**<0.001**
Pressure	Mean Pressure	TD	4.91	-0.66	10.54	0.093
		TD + D	9.13	1.67	16.33	**0.012**
	Mean Speed of Pressure Change	TD	5.43	-1.03	11.92	0.09
		TD + D	23.45	15.66	31.55	**<0.001**
	SD of speed of Pressure Change	TD	17.81	11.35	24.28	**<0.001**
		TD + D	29.96	22.09	37.89	**<0.001**
Tilt	Distance to Mean of Tilt-x Freq.	TD	-1.84	-6.21	2.87	0.424
		TD + D	-18.76	-24.55	-13.49	**<0.001**
	Bandwidth of Power Spectral of Tilt-x Freq.	TD	0.31	-5.89	6.87	0.929
		TD + D	-12.96	-19.65	-6.26	**<0.001**
	Median of Power Spectral of Tilt-y Freq.	TD	4.41	-1.23	10.52	0.118
		TD + D	19.59	13.96	25.94	**<0.001**

Time Ratio or the SD of Handwriting density is with an increase in the quality of handwriting (i.e., the lower the score is, the better the quality is). Separately, the Median Power Spectral of Speed Frequency was negatively correlated with the BHK quality score-in other words, the higher the value of this feature is, the better the handwriting quality is.

Speed association Concerning the BHK speed score, the same three features were significantly correlated with the BHK speed score of TD children.

A fourth one namely, the SD of Speed of Pressure Change, was also found to be significantly associated (see Table 4.5). The Median of Power Spectral of Speed Frequencies was found to be negatively correlated with the BHK speed score, meaning that, the lower this feature is (indicating a less brutal change in handwriting speed), the higher the speed of handwriting will be.

In the same way, the In Air Time Ratio was found to be negatively correlated with the handwriting speed (a reduction in the time the child has the pen not touching the paper will result in more time spent writing and thus a higher handwriting speed) as well as the SD of Handwriting density (which can be interpreted as the fluctuation in the handwriting size). Finally, the SD of Speed of Pressure Change was found to be positively correlated with the handwriting speed. Clinically, this feature can be linked with the automation of the pen movement (i.e., the child has a better control of the pen if he/she is able to change the pressure of the pen in different ways).

Interaction of the digital features with grade Considering a developmental analysis of handwriting, we used multivariate models to predict children's BHK scores (quality and speed), taking into account the digital feature, the grade, the gender, but also the interaction between the feature and the grade. Results of the interaction are reported in Table 4.6 for the BHK quality score and in Table 4.7 for the BHK speed score, respectively.

Quality interaction:

Table 4.6: **Multivariate models with interaction to predict the BHK quality raw score**

Category	Feature	Dataset	Feature * grade estimate	CI95% low	CI95% up	p value
Static	Space Between Words	TD	-0.72	-1.18	-0.31	**0.001**
		TD + D	-1	-1.62	-0.38	**0.001**
	SD of Handwriting Density	TD	-0.77	-1.2	-0.35	**0.001**
		TD + D	-0.44	-1.06	0.26	0.197
	Median of Power Spectral of Tremor Freq.	TD	0.22	-0.17	0.6	0.237
		TD + D	0.16	-0.35	0.63	0.527
Kinematic	Median of Power Spectral of Speed Freq.	TD	0.52	0.08	0.92	**0.003**
		TD + D	-0.42	-1.27	0.34	0.357
	Distance to mean of Speed Freq.	TD	-0.5	-0.89	-0.07	**0.04**
		TD + D	-0.8	-1.48	0.09	0.073
	In Air Time Ratio	TD	-0.48	-0.92	-0.03	**0.04**
		TD + D	-0.15	-0.78	0.53	0.637
Pressure	Mean Pressure	TD	-0.18	-0.57	0.2	0.333
		TD + D	0.26	-0.23	0.75	0.313
	Mean Speed of Pressure Change	TD	0.54	0.04	0.94	**0.023**
		TD + D	0.45	-0.29	1.14	0.216
	SD of speed of Pressure Change	TD	0.82	0.38	1.24	**0.001**
		TD + D	0.46	-0.15	1.05	0.12
Tilt	Distance to Mean of Tilt-x Freq.	TD	0.02	-0.36	0.42	0.891
		TD + D	-0.52	-1.2	0.3	0.218
	Bandwidth of Power Spectral of Tilt-x Freq.	TD	0.43	0.03	0.84	**0.028**
		TD + D	-0.11	-0.81	0.59	0.774
	Median of Power Spectral of Tilt-y Freq.	TD	-0.05	-0.53	0.44	0.852
		TD + D	-0.09	-0.76	0.58	0.755

The higher the score, the lower the handwriting quality) for typically developing children (TD dataset) and all children together (TD + D dataset).

Once again, we can see that the interaction between handwriting digital features and grade seems to be different between children with dysgraphia and TD children. If we consider the features of the TD children alone, eight of the 12 features present a statistically significant interaction with grade to predict BHK quality, while only one (Space Between Words) is significant if we add the children with dysgraphia to the dataset on which the model is applied (Table 4.6). We believe that this can be explained by the fact that children with dysgraphia show a very different handwriting manner (and thus very different digital features) and present a significantly higher heterogeneity in their writing (and thus more spread-out) as compared with TD children, which brings additional noise to the model and avoids us from finding significant interactions.

For the same reasons as before, we decided to focus our interpretation on TD children only. As can be seen in Fig. 4.3 and Table 4.6 an interaction between most of the digital features with the grade was found to predict the BHK raw quality score. Only two tilt features (Distance to Mean of Tilt-x Frequencies, Median of Power Spectral of Tilt-y Frequencies), one static feature (Median of Power Spectral of Tremor Frequencies) as well as one pressure feature (Mean Pressure) did not present a statistically significant interaction with the grade. This result shows that the predictive value of most features changes with the grade. In other words, most of them are either useful for detecting the quality of the writing for the younger or for the older children. A typical example of this can be found with the Space Between Words: this feature is positively associated with BHK score in first grade and becomes negatively associated by fifth grade (see Fig. 4.3). In other words, as the child is progressing in his/her school curriculum, the Space Between Words feature becomes more and more so a negative predictor of the BHK quality score (and thus a positive predictor of handwriting quality).

Speed interaction: Models with interaction between features and grade to pre-

Table 4.7: **Multivariate models with interaction to predict the BHK speed raw score for typically developing children (TD dataset) and all children together (TD + D dataset).**

Category	Feature	Dataset	Feature * grade estimate	CI95% low	CI95% up	p value
Static	Space Between Words	TD	1.24	-2.81	5.33	0.52
		TD + D	8.64	3.25	13.96	**0.003**
	SD of Handwriting Density	TD	-0.1	-4.37	4.69	0.948
		TD + D	-3.14	-8.97	3.58	0.318
	Median of Power Spectral of Tremor Freq.	TD	1.22	-2.21	4.87	0.514
		TD + D	-2.47	-6.66	1.65	0.203
Kinematic	Median of Power Spectral of Speed Freq.	TD	3.27	-0.02	7.39	**0.039**
		TD + D	-4.4	-10.83	3.09	0.223
	Distance to mean of Speed Freq.	TD	-4.32	-7.62	-0.5	**0.038**
		TD + D	-7.85	-15.72	-0.53	**0.005**
	In Air Time Ratio	TD	-2.29	-6.46	2.12	0.279
		TD + D	-9.29	-14.64	-3.69	**0.001**
Pressure	Mean Pressure	TD	3.89	0.55	7.61	**0.028**
		TD + D	2	-2.19	6.26	0.337
	Mean Speed of Pressure Change	TD	-2.11	-6.14	1.96	0.306
		TD + D	2.84	-2.28	8.47	0.299
	SD of speed of Pressure Change	TD	1.56	-2.03	5.32	0.391
		TD + D	5.7	1.28	10.28	**0.009**
Tilt	Distance to Mean of Tilt-x Freq.	TD	-2.52	-6.27	1.83	0.206
		TD + D	-3.64	-10.46	1.68	0.209
	Bandwidth of Power Spectral of Tilt-x Freq.	TD	-1.93	-6.54	2.78	0.407
		TD + D	-0.64	-6.59	4.93	0.832
	Median of Power Spectral of Tilt-y Freq.	TD	-1.94	-6.09	2.19	0.346
		TD + D	4.43	-1.15	9.8	0.111

dict BHK speed are presented in Table 4.7. In the TD dataset, two kinematic features (Median of Power Spectral of Speed Frequencies and Distance to Mean of Speed Frequencies) and one pressure feature (mean pressure) showed a significant interaction. When models were applied in TD+D dataset, two kinematic features (Distance to Mean of Speed Frequencies and In Air Ratio), one static feature (Space Between Words) and one Pressure feature (SD of Speed of Pressure Change) showed a significant interaction with grade to predict speed.

Interestingly, Space Between Words is the only feature that interacts with grade to predict both BHK quality and speed in the TD+D dataset. It becomes increasingly positively correlated with the BHK speed score with the increase in the child's grade, which means that, at the beginning of the school curriculum, the space that children put between words is not a significant predictor of handwriting speed, but becomes a stronger one as the child continues in his/her school education.

4.3.3 A new clustering of dysgraphia

Most of the classifications of dysgraphia are based on comorbidities (e.g., dyslexia, attention problems, motor acquisition problems). A more precise description of dysgraphia should take into account the peculiar objective characteristics of handwriting. To do this, we used a K-means clustering algorithm with our 12 digital features as input. Using the elbow method to explore the best number of clusters, we found that three clusters was an optimal number according to the majority rule (see Fig. 4.4).

Regarding the final model, the Hopkins statistic was 0.35 and the clusters' stability were satisfactory (cluster 1: 0.87, cluster 2: 0.89 and cluster 3: 0.84). As can be seen in Table 4.8, individuals from each cluster had the following attributes:

Children from cluster 1 (n = 13) presented the less severe type of dysgraphia, with girls and older children being over-represented. Their BHK speed score was significantly higher. Also, they tended to have better BHK quality normalized Score (meaning better handwriting quality) (Table 4.8). Concerning the digital features,

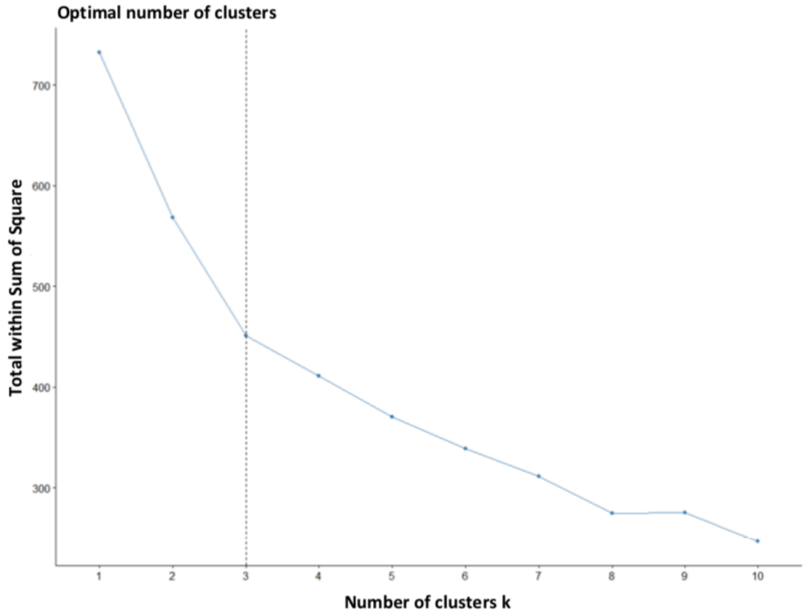

Figure 4.4: **Elbow method to characterize the optimal number of clusters**

it was interesting to see a significantly lower value (as compared with the other two clusters) of the Median of Power Spectral of Speed Frequencies, meaning that the variation of the handwriting speed is slower for these children (i.e., the transition between low and high speeds is smoother). In addition, the SD of Speed of Pressure Change was found to be significantly higher, also suggesting a better automation of the pen movement. An example of this feature can be found in Fig. 4.5, where we can see that the Speed of pressure Change of a child with dysgraphia (from cluster 2) stays relatively constant as opposite to that in the handwriting example of the TD child.

Children from clusters 2 and 3 were all recruited from a specialized clinic, meaning that they presented more severe cases of dysgraphia. As can be seen in Table 4.8, a statistically significant majority of these children were boys, which appears to be in line with the findings of previous studies [3, 72]. Concerning the digital features, children from cluster 2 (n = 25) were characterized as having a lower Space Between Words versus the two other clusters and particular abnormalities in the speed frequencies as well as the pressure features (see Table 4.8). The Distance to Mean of Speed Frequencies was found to be statistically higher here than in the two other clusters, meaning that these children were the most eclectic, regarding the way their handwriting speed was changing. The accelerations (and decelerations) of the handwriting speed were more abrupt, suggesting a lack of automation in the control of the speed (i.e., more jerk recorded). The other features for which children from cluster 2 were noted to be particularly different were the pressure features. As can be seen in the example of Fig. 4.5, children from cluster 2 were using a much smaller gaps of pressure while writing (i.e., the pressure stays relatively more constant during the handwriting) in comparison with TD children.
Children from cluster 3 (n = 24) were characterized by abnormalities in terms of tilt features. As can be seen in Fig. 4.5, children from this cluster had troubles with smoothly changing the inclination of their pen (i.e., the transition between low and

Table 4.8: **Mean digital features value of each features according to their clustering. Demographic characteristics and BHK scores of children with dysgraphia corresponding to the 3 clusters**

Category	Feature	Cluster 1 (n = 13)	Cluster 2 (n = 25)	Cluster 3 (n = 24)	p-value
Statics	Space Between Words	$1.3{\cdot}10^{3}(3{\cdot}10^{2})$	$7.2{\cdot}10^{2}(2.9{\cdot}10^{2})$	$1.4{\cdot}10^{3}(6{\cdot}10^{2})$	**<0.001**
	Median of Power Spectral of Tremor Freq.	$3.2{\cdot}10^{-3}(1.5{\cdot}10^{-4})$	$3.3{\cdot}10^{-3}(9.7{\cdot}10^{-5})$	$3.3{\cdot}10^{-3}(1.2{\cdot}10^{-4})$	0.055
	SD of Handwriting Density	$1.7{\cdot}10^{2}(73)$	$2.3{\cdot}10^{2}(1.3{\cdot}10^{2})$	$2.5{\cdot}10^{2}(1.2{\cdot}10^{2})$	0.161
Kinematics	Median of Power Spectral of Speed Freq.	$1.4{\cdot}10^{-3}(1.6{\cdot}10^{-4})$	$2.2{\cdot}10^{-3}(2.8{\cdot}10^{-4})$	$1.9{\cdot}10^{-3}(2.8{\cdot}10^{-4})$	**<0.001**
	Distance to mean of Speed Freq	$2.1{\cdot}10^{-4}(9.6{\cdot}10^{-5})$	$7.7{\cdot}10^{-4}(3.5{\cdot}10^{-4})$	$4.1{\cdot}10^{-4}(2.7{\cdot}10^{-4})$	**<0.001**
	In Air Time Ratio	$5.3{\cdot}10^{-1}(7.8{\cdot}10^{-2})$	$5.9{\cdot}10^{-1}(1.1{\cdot}10^{-1})$	$6{\cdot}10^{-1}(1.4{\cdot}10^{-1})$	0.104
Pressure	Mean Pressure	$4.6{\cdot}10^{2}(1.4{\cdot}10^{2})$	$3.2{\cdot}10^{2}(1.1{\cdot}10^{2})$	$4.6{\cdot}10^{2}(1.4{\cdot}10^{2})$	**0.001**
	Mean Speed of Pressure Change	$3.1{\cdot}10^{-1}(1.3{\cdot}10^{-1})$	$3.8{\cdot}10^{-2}(3.5{\cdot}10^{-2})$	$6.5{\cdot}10^{-2}(5.6{\cdot}10^{-2})$	**<0.001**
	SD of speed of Pressure Change	$28(7.5{\cdot}10^{-1})$	$13(4{\cdot}10^{-1})$	$20(5.1{\cdot}10^{-1})$	**<0.001**
Tilt	Median of Power Spectral of Tilt-y Freq	$3.3{\cdot}10^{-3}(1.5{\cdot}10^{-5})$	$3.3{\cdot}10^{-3}(3.1{\cdot}10^{-5})$	$3.3{\cdot}10^{-3}(5.5{\cdot}10^{-5})$	**0.001**
	Distance to Mean of Tilt-x Freq	$2.3{\cdot}10^{-4}(3.3{\cdot}10^{-5})$	$2.8{\cdot}10^{-4}(9.6{\cdot}10^{-5})$	$6.3{\cdot}10^{-4}(1.9{\cdot}10^{-4})$	**<0.001**
	Bandwidth_tilt x Freq.	$3.4{\cdot}10^{-3}(2.8{\cdot}10^{-4})$	$3.5{\cdot}10^{-3}(3.8{\cdot}10^{-4})$	$4.4{\cdot}10^{-3}(2.9{\cdot}10^{-4})$	**<0.001**
Clinical description	Grade	4.08 (0.86)	3.32 (1.18)	3.00 (0.93)	**0.016**
	Gender (F/M)	8/5	4/21	6/18	**0.016**
	Laterality (L/R)	0/13	1/24	4/20	0.212
	Recruited in Specialized Clinic	0	25	24	**<0.001**
	BHK quality Score	-2.73 (0.65)	-3.49 (1.25)	-3.44 (1.41)	0.109
	BHK speed Score	0.46 (1.16)	-1.24 (1.00)	-1.10 (0.91)	**<0.001**

The clustering was done on the digital features only

high speeds of tilt change was found to be less constant versus in TD children).

4.4 Discussion

The clinical annotation of our dataset found 13 (5.63 %) children with dysgraphia in schools. This appears consistent with the 5%-10% prevalence rates reported in the literature as well in the most recent French study [72]. Among these 13 cases of dysgraphia, one child was currently in the first grade. This aligns with the fact that children who are referred to specialized clinics for dysgraphia are usually older. This could be explained by the delay existing between the handwriting training and the early signs of alerts that lead to referrals (in France, the diagnostic of dysgraphia is not recommended prior to the second grade).

On the basis of the clinical annotation of the database defining two datasets (TD children vs. children with dysgraphia), a study was performed to investigate children's handwriting acquisition based on BHK clinical assessment [72] and a set of digital features [20].

From the 12 digital features we selected in this work, it was interesting to notice that only three of them were significantly correlated with the BHK quality score of TD children (without dysgraphia), while all of them were significantly correlated when considering the whole sample (TD and D dataset). In other words, it seems that some of the digital features are not useful in explaining the handwriting quality of TD children. From the three features associated with the handwriting quality of TD children, two of them describe handwriting on a kinematic aspect and one describes such on a static aspect. None of them were features associated with the pressure or tilt aspect of handwriting, while these are strongly associated in children with dysgraphia [20, 250]. These results suggest that the pressure and tilt aspects

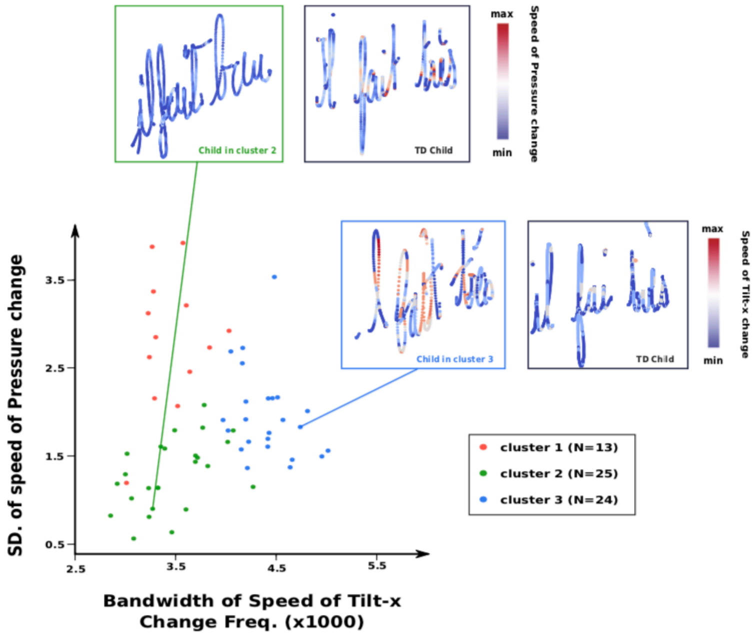

Figure 4.5: **Comparisons of the SD of speed of pressure change and Bandwidth of Speed of Tilt-x Change Frequencies for the children without dysgraphia from the 3 different clusters. Examples of writing from a child with the most severe difficulties from cluster 2 and cluster 3 are shown.**

of handwriting may be particularly central aspects of dysgraphia [20, 311, 368].

In terms of clinical relevance, our findings show the limitation of the current clinical tests used to assess handwriting quality, as the digital features are for the moment neglected due to the technology used (pen and paper tests). They also prove the benefit digital tablets can bring in the assessment of handwriting. In terms of remediation, it may also be particularly interesting to place more emphasis on these aspects of handwriting, for example by using gaming activities designed on digital tablets in which pressure or tilt can be integrated and manipulated. Indeed, in other fields of learning (e.g., emotion recognition; attention), serious games have shown great attraction and clinical interests for children with neurodevelopmental disorders [53, 149]

In contrast with traditional classifications of dysgraphia that are based on children's comorbid problems such as dyslexia, attention deficit or motor-coordination impairment like in the Deuel classification, [103], we established a new clustering of children with dysgraphia based on low-level motor aspects of handwriting including static, kinematic, pressure and tilt features. The K-means clustering based on our 12 digital features yielded three different subgroups. Cluster 1 gathered children with the less severe cases of dysgraphia, including more girls and those with normal speeds. Clusters 2 and 3 included children with the most severe cases of dysgraphia with a preponderance of boys. Children in cluster 2 presented abnormalities in terms of kinematics and pressure, while children in cluster 3 displayed abnormalities in terms of tilt. We do not know whether the clustering introduced in this paper overlaps with existing classifications and in particular the one proposed by Deuel [103], since the sample size each cluster too small to compare the disorders of the children. We hope to perform such a study in the near future. As expected [3, 72], we found that a majority of children with dysgraphia were boys (71%) [72, 103, 343]. The most severe clusters were also the clusters including more boys. Although being left-handed is believed to be associated with handwriting difficulties in folk psychology [148], we did not find that handedness mediated either BHK scores or clustering of the children with dysgraphia.

The current study needs to be interpreted with consideration of both its strengths and limitations. Digital tablets can measure several features that are relevant to better understand and classify children with dysgraphia. On the basis of the results of this study, we plan to move forward with the development of new handwriting tests capable of running on digital tablets (e.g. an Ipad) for the purpose of helping the diagnosis of handwriting-acquisition deficit. However, the handwriting data used in this study were acquired in an ecological setting since the children wrote on a paper attached on the tablet. Several studies show that the friction between a pen and a sheet of paper might be very different from the one of a stylus and the surface of some digital tablets [152]. As this friction difference may have an impact on the handwriting, a new database of handwriting traces should be acquired on a digital tablet to investigate such potential differences.

Secondly, the digital tablets used for the handwriting acquisitions in school and in the specialized clinic were different (Wacom Intuos 3 in specialized clinic vs. Wacom Intuos 4 in school). Despite a careful calibration, the difference in material may have affected some technical aspects of the feature recording. However, to assess whether pressure registration differed between the two tablets, we performed the following experiment: with the pen vertically positioned on the surface of the tablets, 15 different weights were used as an input while the values returned by each tablets were logged. We modelled inputs and outputs in each tablet and between tablets. The correlation found were above 0.99 ($p < 0.001$), meaning that the impact was likely limited [21].

Finally, it is possible that the transversal design of this study cannot allow for the longitudinal assessment of the development of a typical child or a child with dysgraphia from one grade to another. We believe it will be important to assess the evolution of these digital features longitudinally within the same child during learning or rehabilitation.

4.5 Conclusion

In the previous chapters, we showed how we could tackle the limitations of BHK by using tablets to measure and study handwriting features acquired electronically from dynamic measures (Figure 4.6). The current results open new opportunities for the automatic detection of children with dysgraphia more widely available, for instance in classroom. We also believe that the training of pressure and tilt dynamically may open new therapeutic opportunities through serious games able to manipulate these features.

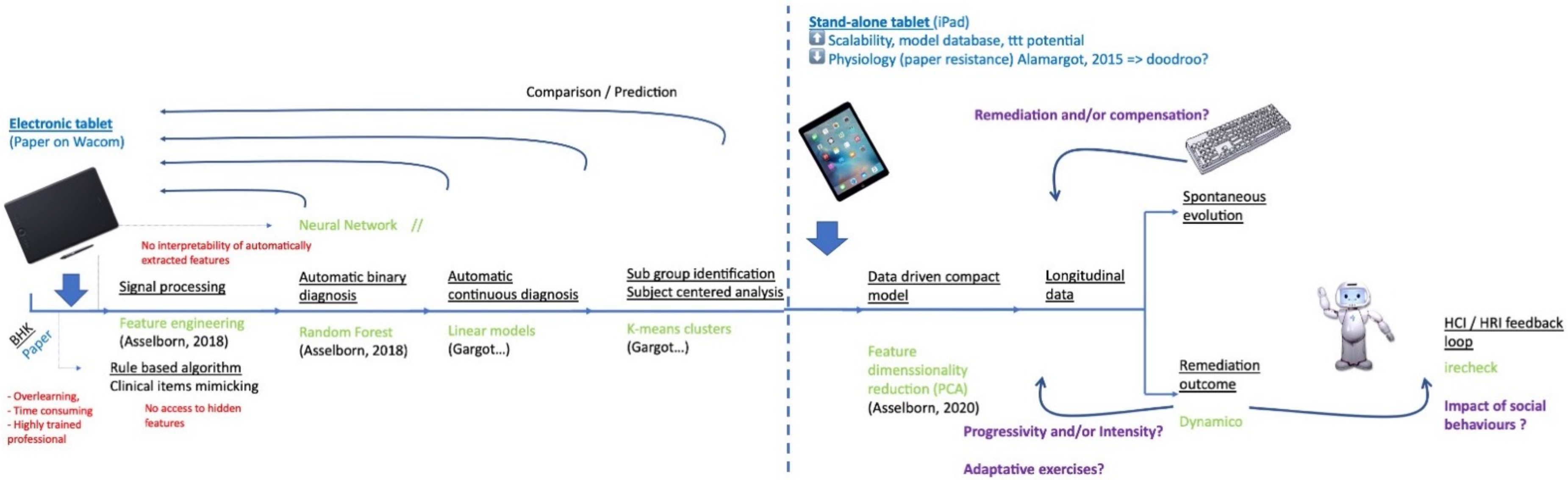

Figure 4.6: **Review of the automatic handwriting features analysis pipeline**

The following chapter, shows how we can use a robotic platform to better understand the process of handwriting longitudinally. We took also into account the measure of the posture beyond the fine motor skill themselves. During a rehabilitation of a clinical case tackling these writing difficulties, we modelized how affective processes in a child-robot interaction could foster the motivation of children. Based on the identification of the different aforementioned domains of handwriting, we proposed specific exercises.

Chapter 5

Tablets to guide the rehabilitation of dysgraphia

Parts of this chapter are published under the title *"The CoWriter robot: improving attention in a learning-by-teaching setup" by Le Denmat, P., Gargot, T., Chetouani, M., Archambault, D., Cohen, D., Anzalone, S. (2018, November). In 5th Italian Workshop on Artificial Intelligence and Robotics A workshop of the XVII International Conference of the Italian Association for Artificial Intelligence (AI* IA 2018)*, and submitted to in Frontiers Psychiatry *"It is not the robot who learns, it is me" Treating severe dysgraphia using Child-Robot Interaction and gaming" (Thomas Gargot, Thibault Asselborn, Ingrid Zammouri, Julie Brunelle, Wafa Jowal, Pierre Dillenbourg, Dominique Archambault, Mohamed Chetouani, David Cohen, and Salvatore M. Anzalone).*

Abstract

Introduction

Writing disorders are frequent and impairing. Rehabilitation requires intensive and long handwriting training in a motivating environment, without fostering anxiety of the children. Social robots may help improving children's motivation and proposing enjoyable and tailored activities.

Materials and methods

Here, we used the co-writer scenario in which a child is asked to teach a robot how to write via demonstration on a tablet.

Results

In a first study, we show that the embodiement of the robot improve the quality of the interaction of adults during a short-term robot interaction. In a second study, combined with a series of serious games we developed to train specifically pressure, tilt, speed and letter liaison controls, we used this set-up in a pilot clinical context. This set-up was proposed to a 10-year-old boy with a complex neurodevelopmental disorder combining Phonological Disorder, Attention Deficit/Hyperactivity Disorder, Dyslexia, and Developmental Coordination Disorder with severe dysgraphia. Writing impairments were severe and limited his participation to classroom activities despite 2 years of specific support in school and professional speech and motor remediation. We implemented the set-up during his occupational therapy for 20 consecutive weekly sessions. We found that his motivation was restored; avoidance

behaviors disappeared both during sessions and at school; handwriting quality and posture improved dramatically.

Discussion

In conclusion, treating dysgraphia using child robot interaction is engaging, feasible and improves writing. Larger clinical studies are required to confirm that children with dysgraphia could benefit from this set up.

5.1 Introduction

Together with the difficulties of a correct assessment of DCD and, in general, NDD including the specific dimension of writing [385], recent studies have shown that several factors can limit the effectiveness of such interventions [94, 266]. Specifically, most of those programs do not target school-aged children and are not proposed to occur in a school setting, a favorable location for intervention on NDD. On the contrary, many treatments are conducted at the hospital in very "artificial contexts", during episodic observations, bringing a "lack of intensiveness" and a "poor individualization" of the intervention. To tackle these issues, the use of technologies has been proposed to achieve a continuous [13, 14, 137, 193], long-term observation of the children, allowing a tailoring of the therapies to the specific needs of the child. In particular, the implementation of new protocols involving Information and Communication Technologies (ICT) can facilitate a gradual shift from hospital settings to more natural environment, ideally the home of children [46]. This shift will push towards a major involvement of the families and possibly an earlier intervention that is highly recommended. At the same time, ICT can simplify the implementation of complex protocol as well as the use of complex devices, such as EEGs, that can be delivered to the families. Technology would also permit a richer understanding of individuals: in classical approaches, the behavior of the child is assessed at the laboratory, during episodic observations; in contrast, ICTs will consent a fine, continuous, long-term observation of the children, allowing a finer tailoring of the therapies, treating each "unique" child for his "unique" problem. Recently, an increasing number of research teams have focused on the use of social robots in behavioral treatment [104, 290, 330]. Although most research in this field may be regarded as preliminary by clinicians, those kinds of robots emerged as an important tool for children because of the various advantages their use could bring to the therapy, regarding:

- **Complexity:** social robots in NDD therapy could simplify the inner complexity of the social interactions. While interacting, people exchange an enormous amount of information in both verbal and non-verbal forms (speech, words, prosody, facial expressions, emotions, proxemics, and so on). As social robots are entirely controlled by robot programmers, the behaviors they can express and the interaction proposed could be very simple and predictable. Clinicians and robotics engineers can take advantage of this, developing new experimental protocols using social robots, focusing just on one or few aspects of the interaction, simplifying the cognitive load required to "decode" such interactions.

- **Embodiment**: social robots can communicate and interact in a multimodal way with children, but, unlikely to serious games, avatars, or other software agents, they have their own "physical presence" in the real world [24, 193, 204, 292]. The embodiment of social robots will permit physical explorations and interactions with the environment [211] as well as a communication with people based also on gestures and touch, widening the possibility of their employment in therapeutic protocols [45].

- **Shape**: android, human-like, animal-shaped, non-anthropomorphic colored toy: the shapes of social robots used in NDD therapies are different, according to their role in the interaction and to the goal of the interaction itself. In any case, the shape of the robot should contribute to the reduction of the stress of the children during the experiment, making them comfortable and at ease [330, 338].

Studies involving social robots in NDD focus on several targets. Scassellati suggested their use as tools for clinicians to diagnose, treat, and understand NDD [329, 330], proposing in particular quantitative metrics of social response for autism diagnosis. According to this idea, several works [13, 45] focused on the use of robots as a convenient instrument of clinical research to induce behaviors on children and widen the description of NDD. Cabibihan proposed also some design requirements that should be considered while developing social robot in the specific case of ASD [56]. Dautenhahn employed social robots as therapeutic tool for children with autism [91], focusing in particular on social interactions [305] and joint attention [306]. Others focused on improving eye contact and self-initiated interactions, turn-taking activities, imitation, emotion recognition, joint attention and triadic interactions. See [290] for a systematic review . The state of the art shows us that social robot have potential to engage children in well-structured and adapted therapy. Together combined with the other metrics from pen and postural data, we believe that we can build a complete system to evaluate and train TD and NDD children to gain better handwriting and fine motor skills.

The CoWriter research project aims to help children with handwriting difficulties using learning by teaching: the child plays the role of the teacher and the robot acts as a peer (a learner) asking for help to improve its handwriting (Fig. 5.1). This approach and has several advantages. Firstly, it increases the child's self-esteem as he/she becomes the one who "knows and teaches", instead of being the worst student in the classroom. Secondly, it has a positive effect on the child's motivation, as he/she feels responsible for the robot [186] and puts more effort to the task. This particular interaction where the child feels responsible of the robot is called the Protégé effect [188, 221]. We hypothetize that this set-up could also be beneficial for patients in their remediation by engaging them longer in the handwriting tasks.

The CoWriter scenario has been used so far during short child-robot interactions in order to evaluate the importance of child-robot setting arrangement [190], child attention [220], speed of learning of the robot [71, 186], as well as effect of collaborative learning [114].

5.1.1 Importance of the embodiment of the robot

In this experiment [217], we explored the role in this scenario of the robot, comparing users performances in three different conditions: handwriting sessions with the CoWriter robot; handwriting sessions with a virtual agent; handwriting session

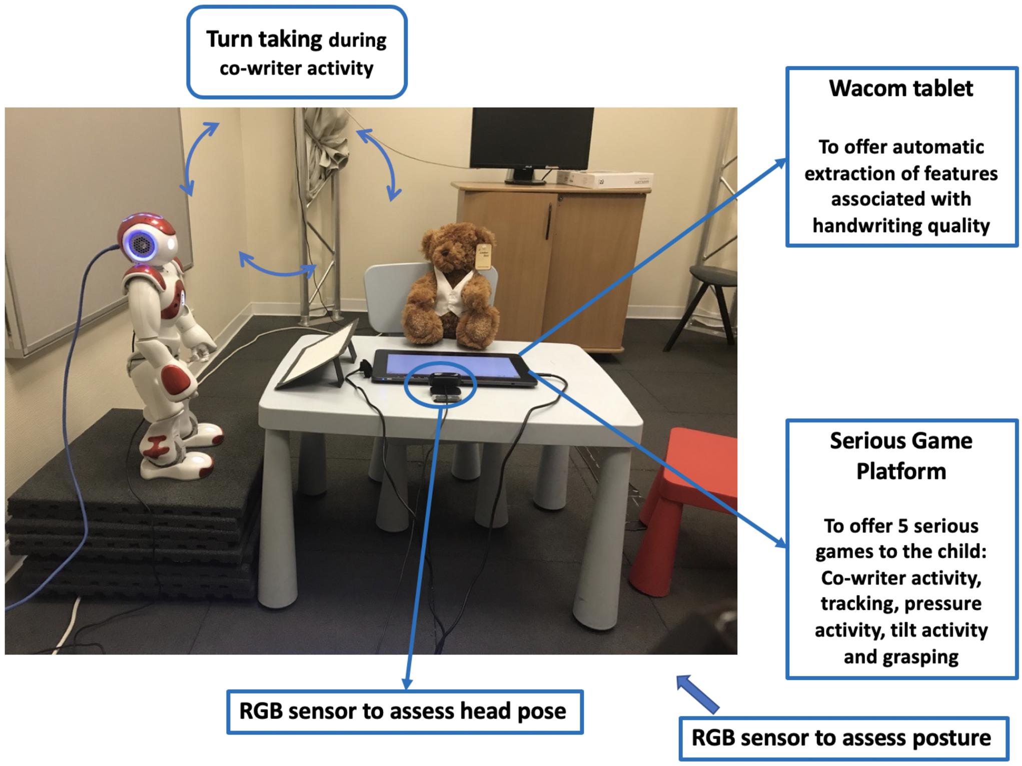

Figure 5.1: The CoWriter set-up: the user teaches the robot how to write.

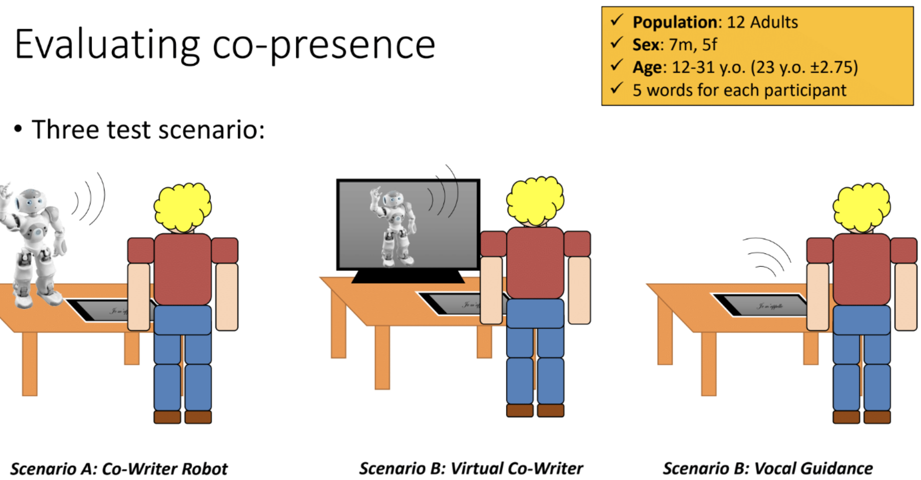

Figure 5.2: The 3 variations learning-by-teaching scenario implemented with 3 different levels of embodiment.

with the tablet only, guided by a voice (Fig. 5.2). The hypothesis is that the social robot would be able to elicit an higher attention than the virtual agent or the vocal guide.

This study highlights that participants feel more the physical presence of the robot than its virtual agent. It is surprising, however, to note the absence of difference between the virtual agent and the voice. Results on the *Attention allocation* highlight how the robot is able to elicit more compliance than the vocal guidance.

It should be noted in this case the absence of difference between the virtual agent and the robot. Such results can also highlight the possibility of the agent of capturing too much the attention of the user, acting as distraction of the task. The absence of difference in the two other dimensions, *Perceived message understanding* and *Perceived behavioral interdependence*, is not strange due to the particular task chose. In particular, the presence of a physical robot or a virtual agent seems does not impact on the comprehension of the exchange. At the same time, it is possible to hypothesize that the interpersonal exchange is too simple to be impacted by the presence of the artificial agents.

5.1.2 "It is not the robot who learns, it is me"

Is it possible to use this set-up during long-term interaction ? Can we use electronics sensors and algorithms to better describe and guide the progress of a child ? In this study, we updated the co-writer software with serious games activities in order to do a step-by-step training and make the activities more diverse and engaging. Thus, we could perform a long-term child-robot interaction in a clinical context.

Patient's characteristics prior training

R. was an 8-year-old boy when he was assessed for severe dysgraphia and refusal to write at school. In the past, he tried to break his pen during writing due to frustration and anger and needed to repeat his 1st grade because of lack of writing acquisition (a practice tolerated in France). Family history showed that R's father and mother had dyslexia. When he was 3 years, R's parents divorced. R's mother broke her coccyx after 5 months of pregnancy. Membranes broke before labor started. R's mother needed a ventilation mask; and delivery needed forceps. Apgar scores were 3, 8, 9 and 10. Weight at birth was 2975 g with normal cranial perimeter and size. A 1-week hospitalization was necessary. After birth, R's mother started a depression. R's early development was marked by psychomotor agitation. He received physiotherapy at age 1 year. He started to walk at 13 months but walking was very instable with a lot of falls. Oral language was subnormal but R had early phonological impairments and he was not understandable when speaking at kinder garden. At age 5 years, he entered a classroom with special education during mornings and received the support of an adult in a classic classroom during the afternoons. At age 6 years, a diagnosis of ADHD was confirmed in a specialized clinic and a treatment by methylphenidate (30mg/day) began after normal cardiac exams. When R. was admitted in our department we conducted an in depth assessment summarized in table 1. He was diagnosed with an Attention Deficit with Hyperactivity disorder (ADHD), a severe dyslexia and a Developmental Coordination Disorder (DCD) with severe dysgraphia that were impairing for schooling. At age 8, he was refusing to use any kind of pens.

In addition to methylphenidate, R received remediation sessions with a reading specialist and was admitted to our special school for multidimensionally impaired children [386]. Given the severity of DCD and dysgraphia, R. also started specific remediation for writing every week (40-minute session) with an occupational therapist. The therapist was limited in R's remediation since he was complaining about writing. The sessions were anxiogenic; he tried to break his pencil when frustrated. The training was progressive to help the child improving confidence and avoid learned helplessness. However, after 1-year the validated testing (BHK) was

Table 5.1: **Patient's characteristics**

Assessment: age	**Results**	**Comments**
Wechsler Intelligence Scale for Children (WISC IV): 7 years	Verbal Comprehension Index: 120 Perceptual Reasoning Index: 107 Working Memory Index: 73 Processing Speed Index: 109	Agitation was important during testing. The cognitive evaluation shows heterogeneous abilities. Verbal abilities were excellent. Attention was poor especially for memory task.
Autism diagnostic Interview-Revised: 5 years	Social interactions: 9 (threshold=10) Verbal communication: 6 (threshold=8) Stereotyped behaviors: 7 (threshold=3) Development score: 4 (threshold=1)	R had subliminal social difficulties and significant repetitive behaviors. Diagnosis of autism was not retained at age 8 from direct assessment.
Language assessment (Age 7 and 8 months)	Oral language Phonology: all scores are pathological (-1.9 to -6.8 SD) from mean Lexicon reception: all scores in the average range. Lexicon expression: normal score for concrete vocabulary, -2 SD for abstract lexicon Syntax reception: all scores in the average range. Syntax expression: all scores in the average range (-1 SD) Written language Reading acquisition has not started yet and assessment is impossible	Severe phonological disorder but good other oral language abilities Severe dyslexia that could only be assessed using tasks for the first trimester of the first grade (6 years in France) in which all scores ranged between 6 and 30 percentiles.
Language assessment (Age 10)	Written language using reading tests based on second grade (6 years in France) Word identification score of non-words is -3.5 SD, of regular words is -2.8 SD, of irregular words is -3 SD. Reading text is painful with time at -0.4 SD, number of errors at -3.5 SD but a comprehension score at +0.9 SD	Severe dyslexia remains. R has entered in the mechanism of reading but with a large delay compared to his age group. Despite this delay some comprehension of written text was possible as +0.9 SD of second grade was the average of 3d grade.
Motor Battery Assessment: 8 years	Degradation score=24 <1st percentile -4.23 standard deviation from mean	Hypotony was obvious and R. had difficulties in motor control. Manual dexterity was difficult. R. needed to stop his breathing to focus correctly. The grasping of the pen was hypotonic and the pen fell many times. R was right handed.
Writing BHK: 8 years	The BHK could not be scored because of too poor quality. (max score = 65)	R. could not write in cursive letters. He wrote some capital letters. The movement was chaotic like he was throwing the pen. Some letters were impossible to read.
Writing BHK: 9 years	The BHK could not be scored because of too poor quality. (max score = 65)	The second testing remained very challenging. Only the 5 first lines were realized and R. wrote only in capitals instead of cursive. The size of the letters was very large.

still impossible to score and R refused to use a pencil in classroom. We therefore discussed with R. and his parents to train handwriting with the Co-writer set up.

5.2 Methods

5.2.1 Co-writer set up

The Co-writer set up was built in order to combine functional training and cognitive/affective processes during remediation (Fig. 5.7). The goal was to stimulate in parallel relativizing and responsibility, on one hand, and handwriting training, on the other hand. The global architecture of the set-up is detailed in a video demo summarizing the 20 sessions available at https://youtu.be/0iLScP0PjzU. The first component of the set-up is a software that allows the extraction of handwriting automatic features (static, kinematic, tilt and pressure) from a computer tablet during writing. The Wacom tablet (Wacom Cintiq pro) allows the extraction of the pen's position (x, y), the pen tilt in 2 axis as well as the pressure between the pen and the surface of the tablet. The sampling frequency of the tablet can go up to 200 times per second (Hz). Features can be extracted that can successfully describe handwriting (cf. Chapter 3 and 4). The second component is a robotic platform Nao that stays besides the child. We previously showed that participants' engagement was better with a physical robot than an avatar [217]. During sessions, the child writes with a stylus on a Wacom Cintiq Pro connected with a laptop. Ubuntu was installed on the laptop with the Cowriter software [170]. We ask the child to teach Nao how to write. One after another, Nao pretends to write on the Wacom tablet by moving its arm and the child write on the tablet to correct the writing of the robot. The cowriter research project aims to help children with difficulties using an original approach: the child plays the role of the teacher and the robot acts as a student requiring help to improve its handwriting. This approach is called learning by teaching and has several advantages. First, it brings a positive reinforcement of the child's self-esteem as he/she becomes the one who "knows and teaches" and not anymore the worst student in the classroom [309]. Second, we can observe a huge gain of motivation as the child, feeling responsible of the robot, is committed to the task with an intensive way higher compared to when practicing in a normal environment. This particular interaction where children feel responsible of the robot is called the protégé effect [74]. Various researches have shown that learning with a physical robot can be more efficient than learning from a more classical approach [160, 176]. We hypothesized that this set-up could be more engaging for the patient than a classical pen and paper remediation. Furthermore, one of the best drivers of training is evaluation [67]. The teaching procedure is one of the more obvious situation during which oneself needs to evaluate its own abilities.

The third component of the set-up is the possibility to access a list of serious games computed in the tablet (Figure 5.4). The games evolved progressively based on the feedback from the child and the therapist. As we said previously, during the Co-writer activity, a robot writes a word in cursive with a bad handwriting. The goal of the child is to correct the robot by showing a "good handwriting". The robot then learns from the child's handwriting and adapt its handwriting accordingly. The difficulty of the activity can be adapted by changing word's length, frequency and writing difficulty and the speed at which the robot 'learns'. The other games –

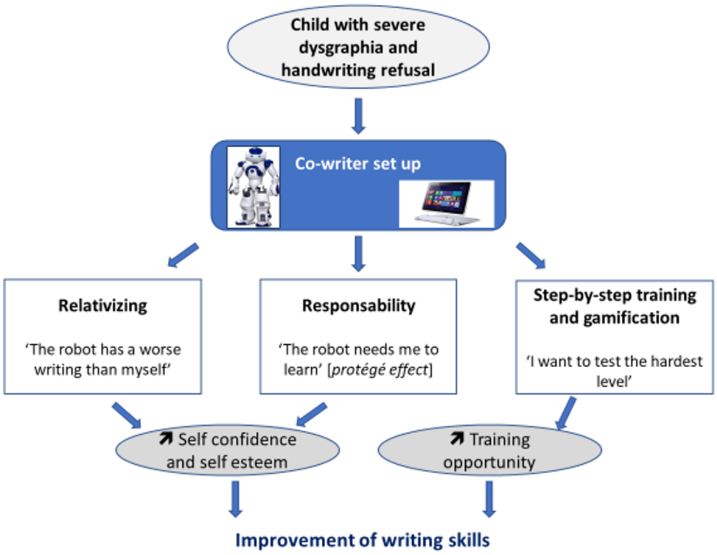

Figure 5.3: **Cognitive and affective processes and functional training involved in the Co-writer set up.**

Dynamico – were computed based on the fact that children with dysgraphia may be distinguish from typically developing children by characteristics related to speed, tilt and pressure when writing [20,132]. We computed new activities to specifically train these skills. During Tracking (Fig. 5.4 B), the robot and the child are doing a track by following a layout in which we can find hidden letters. It is possible to change the level of difficulty of the activity by changing the hidden letter, the speed of the robot purchasing the player and the width of the path. During Pressure activity (Fig. 5.4 C), inspired by Flappy bird game [1] the child is controlling a robot's head by moving the pen from left to right (between the sign start and the finish line) to control the x position of the robot while the y position is controlled by the amount of pressure the child apply between the pencil and the tablet. In order to avoid the obstacles within the game, the child needs to learn controlling the amount of pressure he is applying on the tablet. The difficulty of the activity can be adapted by changing the width of the aperture (the gap between bottom and upper wall) and the number of peaks. During the Tilt activity (Fig. 5.4 D), the child is using the pen like a joystick to control the robot head along the x and y axis. The goal of the activity is to capture the battery in order to recharge the robot while avoiding the bombs. It is possible to increase the level of difficulty by adding more bombs and diminishing their distance with the battery. Finally, the rainbow activity allows making obvious the pauses during handwriting (Fig. 5.4 E). In a turn taking with the therapist that mirrors the co-writer activity with Nao, the child writes alternatively on the tablet. First, the therapist writes a word (or a small text). Each time, there is a lift of the pen, the color of the ink is changing. The child then needs to write the same word (or text) with the goal of reproducing the same color. If the color match between the two words (child's one and therapist's one), it means that the child writes while performing pauses and liaisons in an optimal way. The forth component of the set-up is the therapist who controls the rhythm of the therapy session, decides whether

[1] https://flappybird.io/

or not Nao gives feedbacks (e.g. "Come on, try again"), but can also participate in the gaming session when the child appears bored to play with Nao or asks to play with the therapist the grasping game. One after another, the therapist and the child need to grasp a fruit from a randomly chosen color and avoid the fall of all fruits (Fig. 5.4 F). Finally, the set up includes also two 2D cameras to follow posture and face and offer specific metrics.

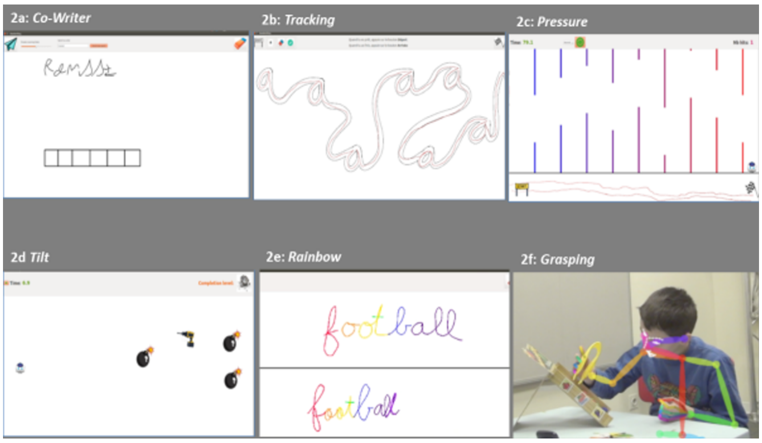

Figure 5.4: **Screenshots from the tablet showing the different games used for handwriting training: A. Co-writer activity; B. Tracking; C. Pressure; D. Tilt; E. Rainbow; and F. Grasping.**

5.2.2 Experimental design and metrics

To assess longitudinally how R. behave during therapeutic sessions with the Co-writer set up, we monitored the sessions and registered several metrics, either clinical or digital as both can be complementary to describe with more details the motor difficulties of children with dysgraphia [132]. We assess: (i) the acceptability and feasibility of the devises, software and set up in a clinical setting using a qualitative approach with an observer listing all significant events and R's comments during sessions; (ii) how did handwriting improved according to digital metrics and the gold standard clinical testing of handwriting called BHK [72]; (iii) how the posture of the child tracked with a 2D camera evolve through remediation as it is known that children with dysgraphia show posture impairments during handwriting [121]. To assess writing, we collected BHK every 5 sessions. Each clinical BHK was randomly and blindly scored by two experts. We also computed several digital metrics to monitor R's progress within each game. Table 2 summarizes each metric per game. Finally, we recorded R's posture. The posture the child assumed during the handwriting session has been extracted and evaluated by analyzing high definition videos (25 FPS) of the BHK writing assessment (5 min writing of the same text). The camera was conveniently placed at 1.5 m of distance in the front-left of the child. Videos collected were analyzed frame-by-frame through the OpenPose library (Figure **??** A) [64, 341] to extract a fine temporal evolution of the child skeleton. For each frame, the skeleton is composed of 94 key points in the (u,v) image space representing the position in the image of the body, of the hands and of the facial landmarks of the child. Notably, for each extracted point, the OpenPose library

Activity	Possible metrics	Metrics shown in Fig 5.6
Co-writer	Word length	During the cowriter activity, we tracked the average number of letters used in the word chosen with the child to teach the robot. Shorter words are easier than longer one.
Tracking	Ratio between the number of points recorded outside the path and inside the path Time required by the R to reach the end of the path (speed)	During tracking activity, we tracked the success ratio and the child speed. A success corresponds to the fulfillment of the tracking task respecting the imposed path without the child leaving the path. Since it was a race with the robot, the cursor speed (here the head of the robot) was also tracked.
Pressure	Level of difficulties to reach the maze Time required by the user to reach the end of the maze	During the pressure activity, we tracked the difficulty and the time to reach the maze. The child was able to choose the difficulty of the exercise. An easier maze was a maze with more space between the obstacles and a more difficult one with a smaller space.
Tilt	Number of collisions with the bombs. Time spent before success	In the tilt activity, due to the very high success rate, we tracked the time to finish the maze.
Rainbow	Difference between the number of strokes recorded by the therapist and the child	

exposes a confidence measure (p). The temporal evolution of the key points is then reconstructed using the framerate of the camera. To assure a reliable comparison between the metrics extracted from different videos captured in different days, the camera was fixed in its specific position thanks to markers on the floor. Moreover, to minimize further possible errors, data were normalized among videos using the distance between the child's left eye and his left's ear as fixed, reliable reference, simple to compute. A metric indicating the quality of the child's posture was defined as the distance between his nose and his right-hand since R. was right-handed. This metric can be interpreted as a reflection of the body posture in the median anatomical plane. Small measures would indicate a head close to the table, while larger ones would suggest a better seat in his chair. Outliers were extracted and removed from the temporal evolution of the defined metric through a rolling window based median filter and through the exclusion of aberrant samples lying outside ± 2 σ (standard deviation).

5.3 Results

R. immediately engaged with Nao. During the first sessions he appeared to really believe in the scenario: he asked "where does Nao come from?", "does he have siblings?" He felt competitive and wanted to show him. Then progressively he understood that Nao 'knew' how to write but was here to help him improving handwriting: "It is not the robot who learns, it is me". In the next sessions, he focused on gaming proposals but Nao sometimes intertwined to support him and he smiled. During the 20 sessions of training, he tried all games, improved dramatically his behaviour regarding schooling and improved his handwriting. Figure 3 shows BHK scores according to time. Both writing quality and speed improved with time. As expected when R. tried to write faster, quality decreased for a brief period of time. At the end of the 20 sessions, around 500 minutes, he was now ready to go back to a regular school where he received special education (see video demo at https://youtu.be/0iLScP0PjzU).

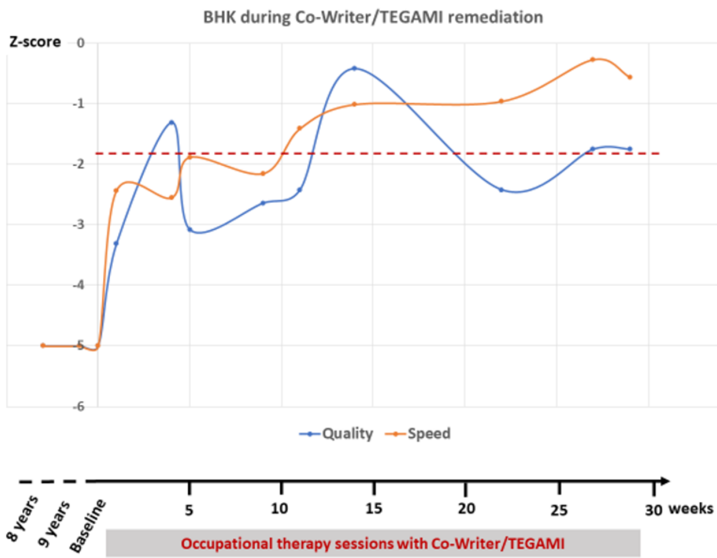

Figure 5.5: **Clinical BHK scores according to time during occupational therapy sessions with Co-Writer/Dynamico.**The z-score shows how many standard deviation the handwriting quality/speed is compared to other children of the same gender and age. A child is diagnosed with dysgraphia when his score is below -1.8 (dot red line). Of note, during the 30 weeks of treatment, R. had 20 sessions in total because of during vacation remediation stops.

Digital low-level metrics are summarized in Fig. 5.6. During the Co-Writer activity, R. was writing short words composed of simple letters like "man" at the beginning of the therapy, while progressively writing longer and more complex words like "jamais" (never) at week 10 or "football" or "serpent" (snake) at week 30 (Fig. 5.6 A). During the Tracking activity, despite some fluctuation in the metrics that paralleled an increase of robot's speed between week 10 and 30, we found an increase of both success ratio (which appears to be a proxy of precision) and R's handwriting speed (Fig. 5.6 B). During the Pressure activity, the time to reach the end of the maze (being a proxy of R. proficiency in the exercise) stayed relatively constant in average (around 15 seconds) despite a clear increase of the exercise difficulty (Fig. 5.6 C). This shows an improvement in the performance of R. along the 30 weeks of therapy. During Tilt activity, we found no increase of the time R. was taking to collect the five batteries (Fig. 5.6 D).

Finally, R improved his posture during the sessions. As shown in figure 5, the distance between nose and right hand increased from week 1 to week 30: at the beginning of the treatment, R's head was close to the paper when he was writing with an average distance of 21 cm. At the end of the treatment, the average distance increased and the child was less bended on his writing sheet with a distance close to 30 cm.

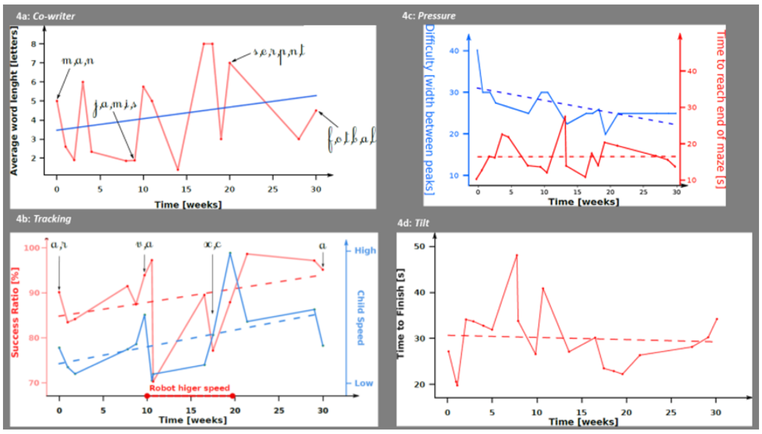

Figure 5.6: **Digital metrics according to time during occupational therapy sessions with Co-Writer/Dynamico A. Co-writer activity.** Average number of letters in the words written by R throughout the sessions. The blue line represents the evolution of the average number of letters computed with a linear regression. **B. Tracking activity.** In red, the Success Ratio (ratio between the number of points recorded outside and inside the path); in blue, child's speed computed as a number of pixel per seconds. The dash lines represent the linear interpolations of both the success ratio and child's speed. During weeks 10 and 20, the robot's speed was increased by the therapists. **C. Pressure activity.** In red, the time to reach the end of the maze; in blue, the width between the peaks (which is a proxy of the maze difficulty). The dash lines represent the linear interpolation of both the activity's difficulty and the time to reach the end of the maze. **D. Tilt activity.** In red, the time to finish the activity; the dash lines represent the linear interpolation of the time to finish the activity.

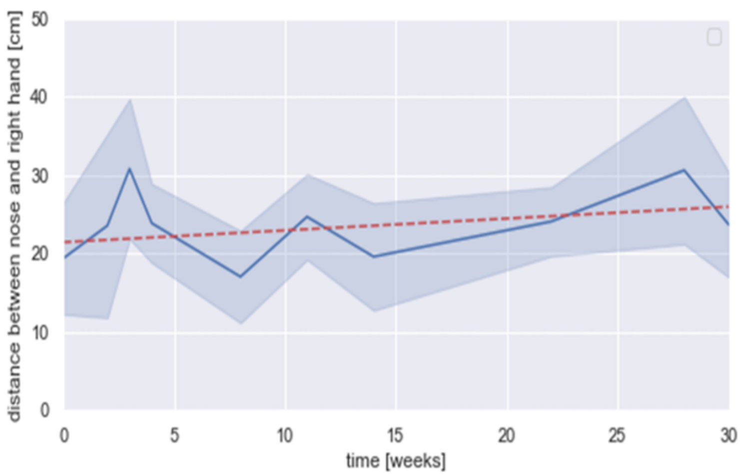

Figure 5.7: **Distance between nose and right hand (cm) according to time during occupational therapy sessions with Co-Writer/Dynamico** Mean (in dark blue), standard deviation (in light blue), linear regression (in dot red) = [0.15 x + 21.44] (R2=0.038)

5.4 Discussion

We performed a long-term child-robot interaction to train successfully the writing of a child with a complex neurodevelopmental disorder. The principle of the treatment was to stimulate in parallel relativizing and responsibility through a protégé effect scenario [74] and learning by teaching [188], on one hand, and handwriting training using serious games with activities to train specifically pressure, tilt, speed and letter liaison controls, on the other hand [20, 132]. The design was iterative, and patient-centered, to strive for a development that would be the most relevant for the end-user [155]. The use of this longitudinal methodology has been made possible by the integration of several domains of expertise related to clinical science, development, computer science and robotics [251]. Interestingly, R's Improvement of writing (figure 1) followed the usual course of writing learning with steps first of quality improvement then speed improvements [3, 72, 232, 326]. He also changed his posture during his writing progress as expected in learners that mature with writing [121]. Regarding our serious games, we proposed numerous features that were sensitive to changes and that paralleled clinical improvement. We hope in the future to compute a novel version of the serious game including tailored feedback based on these features to guide writing training and monitor the progresses of the child in a more autonomous way [119]. These features congruent with the theoretical framework of digital phenotyping have the advantage to be motor and thus easier (even if tedious) to track [182]. Other serious would need to be implemented. Before holding a pen, it could be important to train the grasping on the tablet while performing visuo-motor tasks. Beyond variability, it looks important during handwriting to maintain a stable tilt, which is quite conserved during handwriting, that could be trained with appropriate games. The usability of the set up was good for the therapist and the child, and the system was not invasive even after weeks of sessions showing the promise of robotics in education [33]. Beyond the acceptability and feasibility this framework, we cannot generalize it or suggest some of its ingredients as a treatment of dysgraphia due to the limitation of a single case longitudinal methodology. Even if the failure of previous approaches to treat R's dysgraphia makes alternative hypothesis clinically unlikely [36], we cannot formally exclude a spontaneous resolution of dysgraphia. A randomized controlled trial with sufficient power will be necessary to do such claims of efficacy. Furthermore, it would be useful to assess the relative importance of either the complex system with a social robot or the writing tablet serious games alone. We also believe that using the serious games – Dynamico – implemented on much easier tablets (e.g. Ipad) would be of interest for scalability [119]. In this study, we performed analysis on low-level features that allowed giving real-time feedback during serious games directly based on position, pressure, and tilt. Future analysis should take into account more high level features such as those described in [20] during BHK itself. They would allow to guide rehabilitation (1) by identifying the cluster of dysgraphia the child is in [5], by describing with more details the evolution of the child, since some exercises are more appropriate at the end than at the beginning of the rehabilitation [34]. The social interactions of the robot had also many limitations. We plan to endow it with more social skills to improve (1) the learning scenario, (2) the quality of the feedback, (3) metacognition and self-reflection of the child and (4) motivation. Affective computing would be useful to assess the answers of child after such behaviors. A key aspect to be improved is also the general ergonomics of the system. While it allowed a rather fast improvement of writing in the case of R., the proposed experience was very heavy for clinical users due to time consuming installation before starting a session, complex wiring and unhandy interfaces. Besides the use of a stand-alone tablet (iPad®) to improve the user interface, we may also improve HRI smoothness with a more stable and social expressive robot (e.g., Qt robot). We conclude that this longitudinal single case shows the feasibility and acceptability of Co-Writer set up. Larger clinical studies are required to confirm that dysgraphia could benefit from this set up. We believe that implementation into classroom as a regular educational proposal may also be a reasonable goal in particular if a version for stand-alone tablets may be computed.

Data Availability Statement

The skelleton analysis pipeline for this study can be found in the OSF website https://osf.io/u6bdz/.

5.5 Conclusion

We showed how we could use the insights provided by the analysis of the features, to develop specific activities to remediate handwriting. It will be important to improve user experience of the system for therapists to collect more data. This will enable to confirm and refine the models, to better track the progression of the children and to guide adaptatively the rehabilitation process. This finer analysis could help to better understand the rhythm of the therapy: should the therapist focus on a progressive approach based on fine motor skills training before writing or directly target handwriting which is the goal of the reeducation. Like we showed in the introductory chapter, the rehabilitation for every children should not be the goal if the handwriting training is too difficult and can be substituted properly to keyboard typing without disabling the child (Figure 4.6).

However, the social behaviours of the robot were limited in richness and number. In the following chapter, we propose a theoretical framework (Table 6.1 and 6.2) based on the observation of children. It has implemented but has not been yet tested on the field in a rigorous way (comparative way) nor for a sufficient time (long-term interaction).

Chapter 6

Enhancing the rehabilitation using social robotics

Abstract

Introduction

Handwriting remediation is a long process (> one month). A robot companion could be useful to improve motivation, thanks to the "protégé effect". In the first clinical experiments, the behaviours of the social assistive robot were limited. The long-term interaction emphasized the need of different social behaviours to sustain motivation and engagement in the task and to bypass the "novelty effect". We propose a theoretical and operationalized framework describing such behaviours.

Materials and methods

We conducted two different case studies in 2 different specialized centers treating dysgraphia: (1) one boy was followed for 20 weekly sessions by a psychomotrician, (2) four boys were followed once or twice by ergotherapists. Depending on the children reactions, we implemented iteratively different behaviours and tested them.

Rationale

We propose a library of 21 different kinds of behaviours, organized in 4 categories: (1) the framing of the scenario, (2) give tailored feedback to the child, (3) enhance metacognition and self-regulation skills, (4) promote motivation of the child.

Discussion

This framework allow the implementation of a wizard-of-Oz in Qt creator. Early reactions to the social behaviours are presented but a formal evaluation should be performed.

6.1 Introduction

Building on top of the lessons learned in the CoWriter studies, this chapter describes strategies (and specifically, robot behaviours) for a long-term child-robot interaction scenario aiming at improving handwriting via the protégé effect. Long-term children robot interactions are still technically challenging after the "novelty effect" fades away. Kanda [196] suggested to have a progressive self-disclosure of the abilities of the robot and to allow for discoveries during the interaction. Leite propose to develop empathic behaviours in the robot. [219]. It seemed important to have a robot in the position of a peer. [219]

Specifically, in this article, we discuss how we operationalized and implemented such strategies in a proof-of-concept Wizard-of-Oz (WoZ) set-up, preliminarily evaluated for feasibility in a case study involving 5 participants.

Careful attention is given to the discussion of the rationale motivating our choices in designing the robot's behaviour (in Section 6.3), and in reporting first reactions from the children to this framework (Section 6.4), perspectives (Section 6.5) and limitations (Section 6.5.5).

6.2 Method

6.2.1 Scenario and experimental context

In the CoWriter scenario, a child is first asked to teach a robot how to write. He/she chooses a word, the robot writes it down, then the child is asked to do several fine motor skills activities aimed to train tilt, pressure, speed and letters trajectory. (Figure 5.1). The sessions lasted 45 to 60 minutes. The field pilot studies discussed in this chapter arise from two different case studies:

- **Study 1:** one boy, (10 years old) interacting with the CoWriter set-up with very basic automatic social behaviours for 20 consecutive weekly sessions.
- **Study 2:** four boys (7-9 y.o.) participating in a pilot study to evaluate the feasibility of the introduced social behaviours. Three children interacted with the system for 2 sessions, while one child interacted with the system during a single session of 45 min.

All children were treated for severe dysgraphia, with different diagnosis and often comorbidities (DCD, Autism Spectrum Disorder, ADHD, dyslexia).

6.2.2 WoZ interface

The WoZ interface was developed in Python and QML. A demonstration can be found here https://youtu.be/uwdfpdtqSZQ (Figure 7.1).

6.3 Rationale

The goal of this system is to propose to children with dysgraphia a playful, engaging and efficient reeducation opportunity for their fine motor control skills. We built our rationale for activities that require learning from the child (in our case writing) based on theoretical grounding from psychology chosen from clinical experience with the system, as well as general principles that help a participant to interact with a robot [294]. These include spatio-temporal coordination, coordinated decision making, perception of a partner's effort, adaptative performance of the robot (not too low, not to high), the use of social signals and implicit forms of communications [294].

6.3.1 Framing

Mystification

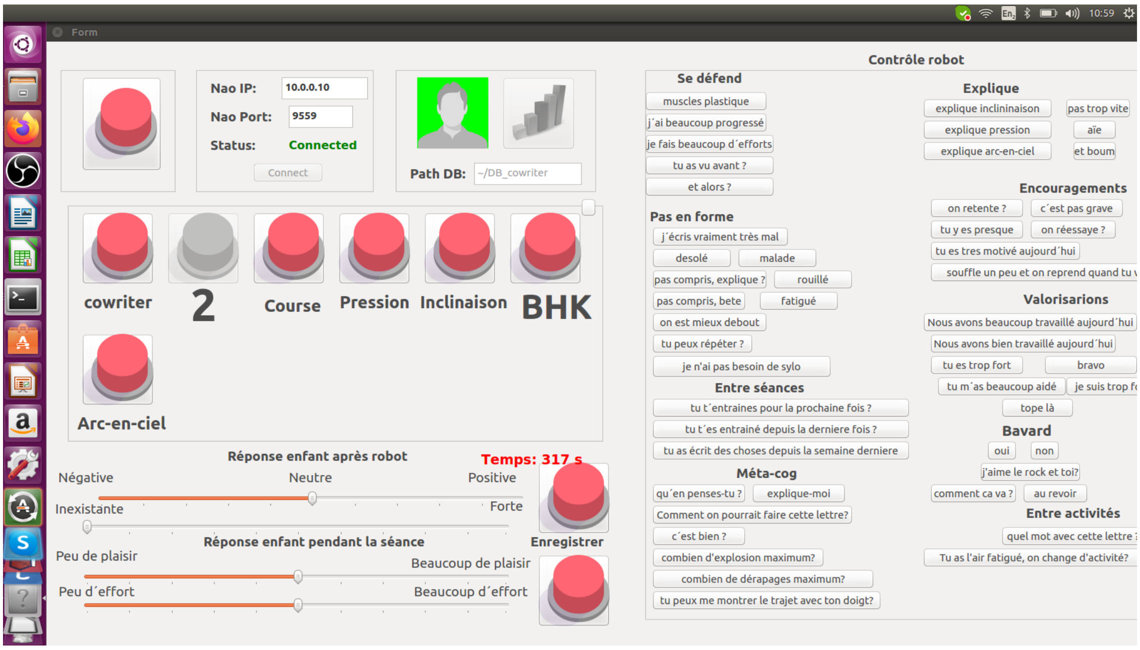

Figure 6.1: WoZ Interface. On the left side, the therapist can connect to the robot (top), choose the activity to engage the child in (centre), and annotate the child's responses to the robot's behaviour (bottom). On the right side, buttons to trigger various robot behaviours.

The child is part of an engaging handwriting activity in which a social robot is able to establish with him a strong empathic link, thanks to an appropriate exploitation of the protégé effect. The emergence of such connection relies mainly on the ability of the robot to be perceived by the child in a believable way: this can be achieved through its coherent participation to the task in an active, reliable and social way. However, endowing robots with such skills in a real, complex scenario, such as the one considered in this work, can be a very difficult task. In this chapter, we rely on teleoperation to overcome the limits of current technologies in the comprehension of the mutual social interaction between the child and the robot. The idea of using teleoperation to remotely control a social robot (and thus give to the participant interacting with the robot the illusion of an autonomous robot behaviour), called *WoZ*, is largely adopted in Human-Robot Interaction studies [302].

In the specific scenario we consider, the complexity of the robotic system can be further reduced thanks to the imagination of children: we do not really need a robot able to write with a pen, because the simple gesture of pointing toward a cardboard cutout of a tablet (preferably built by the child himself) can be enough to maintain the illusion of writing. The robot can explain such special ability: "you know, I don't need a pen".

In general, a background story, a personality and the mystification of the robot's own abilities arouse in children the projection towards the robot of a sort of social intelligence: the robot is not seen anymore as an object but as a kind of "living creature", a companion with a character, its past experiences, its skills, its weaknesses, and the ability of expressing simple emotions [10]. Milgram already studied the belief we can project on teleoperated humans with the cyranoïd concept [253]. This concept is based on a theater play of Rostand, within Cyrano want to court

Roxane but affraid to be rejected because of his long nose ask the handsome but stupid Christian to repeat his love words to seduce her [314]. Interestingly, even if the mystification with a robot can be limited, children seem prone to believe it, engaging the robot accordingly.

Lastly, we also hypothesize that small talk expressions such as “Hello”, “Bye”, “Yes”, “No”, “Can you repeat ?” and using the name of the child would contribute to the projection of social intelligence on the robot and have a positive impact on the child’s engagement with it.

Framing the limits

Our functional analysis (Figure 1.3, in chapter 1) shows that the children could be prone to avoiding motors skills training and writing, as they could trigger negative emotions. Even if avoidance is helpful in the short-term, operant conditioning predicts that it will reinforce the avoidance behaviour and in the long-term, it increases the fear, and the avoidance in a vicious circle [85, 342]. To have a robot which is limited in its behaviour and can not adapt to the short-term needs of the child is relevant since it prevents the avoidance behaviour of the child.

Low performing robot with a humble attitude

The long-term interaction of case study 1 showed some of the technical limitation of the robot (freezing, falling). Instead of trying to fix all of them, we believe that they are congruent with the scenario of a low performer robot, and we made the robot react to them with sentences such as “Ah, finally, I can stand”, “I am sorry, I am tired today”, “I am sick”, “I am rusty”. This allows the child to relativise his/her own writing difficulties. The robot can also amplify a humble attitude that triggers the feeling of responsability in the child.

According to the Observational Learning theory [26] and identification theories [323], children do not only learn by trial and error but also by imitation. This process could be helpful for modelling the request for help and dealing with aggressivity.

Dealing with aggressivity and frustration with humour

Writing can be frustrating for these children. They can be bullied because they can not perform as well as their classmates. We saw that one child was ”bullying” the robot: ”I will throw you by the window”. We hypothesise that he was copying what he was experiencing outside. Thus, reversely, it is important that the robot displays good coping behaviours, as suggestions for the child about how to behave if he/she is mocked or bullied. Examples include: “You know, I have muscles in plastics”, “I progressed a lot”, “I do the best I can”. Whenever the child shows frustration or anger about the task, it is important that the robot expresses empathy (e.g. via statements such as “You seem angry”, “You seem tired, let’s have a break and then start again”).

Congruent audio-motor behaviours

While implementing these behaviours, we also added social postures for the robot which are congruent with the verbal utterances and make the system more believable [363]. See also the posture https://youtu.be/uwdfpdtqSZQ.

6.3.2 Feedback

Increase self esteem by progressive training, clear positive feedback and valorisation

Positive reinforcement is a good strategy to help learning processes and increase self-esteem. The robot can praise the child verbally (“Well done”, “Congrats” [254]) or even physically, calling for a “High five” that could induce a complicity with the child. To label (social labeling) [31] the child is also a techniques that showed promising results. We propose to explicitly include the robot into the loop of positive reinforcement (”We progressed a lot together today”, ”We are so good”) and we call this process valorisation [254] with inclusion, or labelling [31] with inclusion.

Error acceptance and negative feedback

If the child fails with his/her performance, the robot should show support and relativise the behaviour to help him/her accept the error: ”It is ok, it happens”, ”Take a breath and try again”. It is important that the child is able to process and accept the error as an opportunity to learn and to go out of his/her comfort zone [99]. Negative feedback and direct advice are very common but not recommended (”righting reflex” [254]) since they can decrease self-esteem, intrinsic motivation and are incongruent with the scenario.

Multi-sensorial feedback

A visual and auditory automatic feedback was added to denote occurrences of the child performing the wrong action during one of the activities. A clear, repetitive feedback facilitates the training, especially if it is multisensory [245].

6.3.3 Metacognition and self-regulation

According to the Cognitive Orientation to Daily Occupational Performance (CO-OP) therapeutic model [293], motor planning is as important as the execution of the movement itself. A very close technique used in sport is to visualise the movement before executing it [199]. We operationalise this concept in the robot via sentences such as: “How many times maximum you expect to go out of the trajectory during the speed activity?, ”How many bombs do you expect to touch, during the tilt activity?”. The robot can also ask ”Can you draw the trajectory?” to check whether the child has a motion strategy and to differentiate a lack of training from a difficulty of fine motor skills (”I did not understand, can you explain how to do this letter?”). Furthermore, this behaviour can normalise any request for help the child may make [26].

6.3.4 Motivation

Self determination theory states that there exist two kinds of motivation, intrinsic and extrinsic [239].

Intrinsic motivation

Intrinsic motivation is ”an expression of a person’s sense of who they are, of what interests them” [98]. Intrinsic motivation leads to better conceptual learning, greater creativity, more cognitive flexibility, and enhanced well-being relative to extrinsic motivation [317].

We think that the framing is very important to sustain intrinsic motivation, alongside progressive training and session preparation. Concerning the former, Csikszentmihalyi [88] showed the importance of focusing on an activity neither too difficult neither too easy, to reach an optimal flow. Concerning the latter, psychotherapy research on non specific factors identified empathy as a main driver as efficacy [271]. In addition, while consistency and rationalization are important drivers of human behaviour [161], in order to trigger change talk (patient talk consistent with a targeted behaviour [254]), the robot can check and sollicitates behaviour engagement outside sessions (e.g., “How did you train since last time?”, “How do plan to train before the next session?”, “Can you bring me a letter for my notebook so I can have a souvenir from you and an example to train my writing?”).

Extrinsic motivation

Extrinsic motivation ”involves doing an activity because it is instrumental to some separate consequence. [...] Thus, people are extrinsically motivated for an activity when they do it in order to earn money, avoid punishment, or comply with social norms.” [98]. We think that the various types of feedbacks embedded in the system are very important to sustain extrinsic motivation.

6.4 Reactions to the social behaviours

6.4.1 Framing

Case study 1 (long-term single case study) suggests that the mystification is quite powerful. The child greeted the robot (Nao) and asked if it had cousins. This mystification was maintained for several sessions by the child, even after demystification occurred (identified at the time the child said ”It’s not really the robot that learns, it’s me”). From that moment on, the child looked happy to still act “as if” he was really helping the robot. We propose to coin this phenomenon as the “Santa Claus effect”, in which the child is ambivalent about the truth but likes remembering the belief he adhered to at the beginning (just like with Santa Claus and Christmas).

One of the children in study 2 was very avoidant about writing and, at the beginning, only wanted to play something related to trains with the robot. In this case, the limits of the framing (the robot was only here to write and make fine motor skills exercises) were very helpful since they limited avoidance (writing was necessary to interact with the robot). In general, children were very happy of the robot’s low performance and humble attitude and sometimes attacked it (which was frustrating to witness for the therapists).

We hypothesise that, in the case of the child who showed most aggressiveness towards the robot, this behaviour arose from imitating behaviours he could see from other children or adults towards themselves, since he was not “as good” in motor skills as his friends.

6.4.2 Feedback

Positive feedback was observed to facilitate the interaction, helping steer clear from situations that could put the child in learned-helplessness [65]. Specifically, it was very helpful for the children in study 2 to receive a clear motor feedback on their performance (when they tilted their stylus in a wrong direction, when they were going out of the given path in a path-following activity). In contrast, during study 1, the child became over-confident and wanted to do everything as fast as possible, not caring for his mistakes. As soon as feedback was implemented, it allowed him to limit his impulsivity, a trait often found with ADHD, helping him to take time to plan his strategy.

6.4.3 Metacognition and self-regulation

Whenever the children were able to reflect on their performance, instead of rushing towards the end of the exercise, they would decrease their speed and impulsivity and focus on quality (e.g. "I will try to go out of the trajectory 3 times instead of 4, this time" or "I will use this path" in an activity consisting in controlling a cursor with the tilt of the stylus to reach a reward while avoiding bomb obstacles).

Even in study 1, with the robot not equipped with social behaviours, we saw that the children were prone to challenge themselves progressively and move towards harder tasks.

6.4.4 Motivation

The system allowed a good commitment of the child. In the long-term study, avoidance behaviours decreased, such as producing cat vocalisation, or being rigid about the time schedule. The child even asked whether he could show to a friend what he was doing with the robot.

The improvement of the robot's writing was also an important factor of motivation. For instance, the boy of study 1 could be frustrated because the robot was not learning fast enough and he felt helpless because of that. To overcome that issue, we changed the speed of learning of the robot, pushing it to its maximum. The social behaviours to trigger transfer outside of sessions (e.g., "what can you write for me next time?") were not tested long enough to allow for any type of conclusion about their effects.

6.5 Perspectives

6.5.1 Importance of a closed feedback loop

The purpose of this CoWriter set-up, as any other remediation technology, is to have a positive impact on the skill for which remediation is needed. In our case, this calls for very clear metrics to measure the child's writing quality and track its evolution over time. Luckily, the assessment of fine motor skills can be robustly done via the analysis of the pressure, tilt, position and speed of movement of the stylus [20], and research suggests the existence of a strong correlation between fine motor skills and overall handwriting quality, allowing for the definition of "handwriting quality metrics" based on tablet and digital stylus data [20]. It allows a tailored feedback tracking early artefacts (something which is measured and unrelated to the child performance, e.g., we can see such artifacts in Electro-encephalography).

6.5.2 Evolution of the robot's behaviours over time

A crucial factor to sustain effective long-term interactions is the robot's ability to evolve and grow over time, e.g. by displaying increasingly complex behaviours. At the same time, the goal of any remediation technology is to become useless, i.e., to empower its user sufficiently to continue to progress without it. The goal of a social robot is "not to reach the myth of media richness, i.e. the belief that the more a robot interacts as a human (understands language, perceives emotions), the better it will be for learning". The goal is to control the necessary "cognitive load induced by the construction of new schemas" [106]. To tackle these two goals, we think that the robot's behaviours could evolve with time in complexity and frequency, e.g., moving from frequent, simple and automatic feedback at the beginning, to fewer and more abstract social behaviours later on. Along this line, a sign of success of the therapy could be complete removal of the robot in the last sessions, replaced by a stylus and tablet, or even pen and paper.

6.5.3 Robot as a peer

In CoWriter, the robot could be considered as a protégé that needs the child's help ("The robot is even worse in writing than me"), as well as a peer with whom the child is doing turn taking activities and sharing interests ("I like trains, what do you like?"). This role of the peer could be further examined by exploring the experiments in the social facilitation paradigm, in which the performance of subjects increase while being observed by others subjects [351, 365]. While we don't think that it would be beneficial, in our context, to place the robot in the role of an instructor ("In this activity, you need to do that and that") or advisor ("Beware, you are going too fast"), we think that the flexibility to change the role is a key strength. At the same time, we believe that the robot's strongest asset will likely be its humble attitude.

6.5.4 Role of the therapist/teacher

Two different requests emerged from the case studies. The therapists involved in study 2 were asking for a very adaptable and controllable robotic system, allowing them to tailor as much as possible the remediation to the needs of the child. Conversely, in the classroom, the teacher preferred a more autonomous robot, allowing her to focus on the other activities involving other children. The robot in the classroom should therefore decrease the cognitive load on the teacher.

An interesting approach to integrate the two requests in a single framework is the Supervised Progressively Autonomous Robot Competencies (SPARC) approach [333]. In this approach, the robot can learn over time which of its behaviours are relevant, and when, and suggest them to the Wizard (the operator) controlling it, thus reducing its cognitive load while still allowing for full control.

6.5.5 Limitations

6.5.6 Lack of a Field Evaluation

To date, our proposal is mostly theoretical, since we only tested it in pilot observational qualitative studies (study 1 and 2), lacking a rigorous experimental design.

6.5.7 Emergence problem and impact of framing in the long-term

In Figure 1.3 we report the negative vicious loop that describes writing difficulties insurgence and evolution. In the same way, we could draw the positive loop that is activated with remediation. If the child shows an increases in self-esteem, invests more energy on writing and is given a positive reinforcement [342] on his attitude, ultimately seeing that his/her performance improves, then, he/she will be more prone to invest even more energy in writing, by feeling more confident.

However, a complex system like reeducation can induce the emergence of unsolicited behaviours and attitudes that would make this theoretical framework totally or partly inaccurate. Thus, it is important to mix short-term and laboratory approaches to better understand how children learn and are motivated, at the same time taking care of implementation and testing on the field.

6.6 Conclusion

An insight from experimental, especially social, psychology and remediation seems useful to develop a Wizard of Oz social robot to improve education, especially in the case of handwriting, even if the marriage between robotics and social psychology looks unseasy to other researchers [183].

The naive idea of a complex and high performer robot that will be useful for remediation is here theoretically challenged since (1) the scenario and the mystification are fundamental and must be taken into account, (2) a low performer robot is more prone to need help from the child that a high performer robot, (3) the goal is not substitute the teacher (or a therapist) but to alleviate the work overload, to offer more research opportunities, or to perform a specific role, like helping to tackle avoidance behaviours.

However, only early usability data were done and showed that the child could be more engaged with the system when the robot was social.

We are planning to conduct a proper study (with the project IReCHeCk) with this robotic architecture and this scenario with children with severe dysgraphia.

The advantage of taking children with severe dysgraphia even if they are more difficult to recruit and to engage in therapy is that, they could be (1) the end users of the system ; (2) it would be easier to show differences during the remediation since the margin of improvement is larger.

A large data base would also allow (1) to check the relevance of the robot behaviors in the field, what of them are useful, useless, which kind of child behaviours emerge ? Is the long-term interaction sustained ? Is the attachment, separation with the robot a problem ? (2) Is it efficient on writing features in a large sample ? Is a randomized control trial feasible ? What is the optimal profile of the children that would benefit from this system ?

Table 6.1: Design framework used to implement the behaviours to sustain long-term child-robot interaction

Dimension in the model	**Concept and supporting evidence**	**Robot behaviour/proposal**	**Expected effect on the child**	**Child's supporting verbatim or behaviour**
Framing	Cyranoïd [253] ; Wizard of Oz [212]	Deception ("I need help", "I am very bad at writing")	Engagement in the child-robot interaction	"It's not really the robot that learns, it's me"
		Small talk ("Hello", "Bye", "Yes", "No", "Can you repeat")	Engagement in the child-robot interaction	"Do you have cousin ?"
		Naming ("Hello Marcel")	Engagement in the child-robot interaction	"Hello Nao"
	Preventing avoidance, Negative reinforcement [342]	Framing the limits ("You know I am a robot I don't understand much")	Focus on motor skills and writing tasks	"Can we play train with the robot ?"
		Giving instructions ("Can you help me write cat ?")	Focus on motor skills and writing tasks	"Ok"
	Responsability: Protégé effect [188], Relativization	Bad writter ("I am very bad at writing")	Increase self esteem, positive emotional valence	"It is even worse than me"
	Observational learning, Social cognitive Theory [26]	Ask for help ("Can you help me ?")	Engagement in the child-robot interaction	"Yes, I can try"
	Observational learning, Social cognitive Theory [26]	Coping behaviours when attacked	Mimicking good coping behaviours when attacked	"I will through you out of the window"
Feedback	Positive reinforcement [342] Labelling [31]	Valorisation: "High five", "congrats" "You are so good"	smile, engagement in the task, grit, self-esteem smile, engagement in the task, grit, self-esteem	smile, engagement in the task smile, engagement in the task
	Valorisation and inclusion, Positive reinforcement [342] ?	"We progressed a lot together today"	smile, engagement in the task, grit, self-esteem +	smile, engagement in the task
	Error acceptation [99], Relativization	Support: "It happens", "Take a breath, and we try again"	grit	persistance on the task
	Rather unrecommended (Expert position, righting reflex [254] People feel less risk to be judged by an avatar than by a human [197]	Social Negative feedback?; Advice ? ("You go to fast")	increase awareness, increase stress, decrease self esteem	
	Multi-sensorial feedback [245]	Automatic Negative feedback (explosion or skid noise)	increase awareness, increase stress, refine child perception action loop model	Awareness of the child, challenge attitude, decrease impulsivity

Table 6.2: Design framework used to implement the behaviours to sustain long-term child-robot interaction

Metacognition and self-reflection	Plannification / motor imagery [37]	How many bombs you will hit?"	increase awareness, increase stress, refine child perception action loop model	"I just did 4, I will try 3"
	Check strategy and planification [293]	Can you draw the trajectory?	increase awareness, refine strategy, decrease impulsivity-Reaction time	"I will take this path" (while pointing)
	Confidance on the performance	"Is it too easy, or too difficult ?"	increase awareness	"I want to try the harder level"
	Check strategy and planification [293]	"I did not understand, can you explain how to do this letter ?"	increase awareness, refine strategy, decrease impulsivity (Reaction time)	engagement in the task
	Empathy : Reflecting feelings [307], non specific factors [271])	"You look anxious today"	increase awareness	not tried
Motivation	Flow [88]	Push toward other / harder task	Focus on motor skills and writing tasks	"The robot is not learning fast enough"
	Modeling - Observational learning, Social cognitive Theory, [26]	sharing interest	Acceptance on writing task	"ok I can write train, then"
	Congruent speech and behaviour ; Cognitive dissonance [161], Foot in the door [129, 287] ; Change talk [254]	Engagement triggering	Transfer outside reeducation session, make the robot useless	not tried

Chapter 7

Discussions and Perspectives

In this thesis, we showed how electronic sensors and algorithms open new approaches in the way we can describe movement and especially handwriting. This could help to better understand how we learn handwriting. This approach is innovative since it can use previously hidden features, and thus describe more precisely and with a new perspective, a well known process in educational and clinical settings. In addition, we have shown encouraging preliminary results of treatment using these hidden features. Handwriting impairments of some children could be corrected using tailored serious game and a robot as a learning companion.

7.1 Writing and technologies

7.1.1 Handwriting is still important despite the development of keyboards and new interfaces

Despite the development of physical keyboards or keyboards in touch screens, handwriting is still important. During the process of learning, the graphomotor aspects (drawing the letters) help children memorizing and differentiating them, whereas, such movement is not learned while typing and impair the memorization of the letter performance [225]. This effect was only seen in 5 years old children but not in younger ones. The neuronal activities measured by Electro Encephalography (EEG) are also different between handwriting and typing [276]. A recent review, on early writing comparing pen and papers and keyboard showed that the majority of studies indicates that handwriting outperforms keyboarding in early writing [382]. A study showed that the writing process in university, being cognitively costly, required the student to summarize the lessons provided during oral presentations and thus improves memorization compared with taking notes with a laptop [263]. Thus, despite availability of laptops computers and electronic tablets, handwriting is still important to learn the letters and improving memorization.

7.1.2 A better understanding of the current diversity of clinical strategies

We showed in introduction some principles that were studied to validate different writing rehabilitation strategies. From them, we theorised a trade-off between a progressive and an intensive approach that needs to be better understood. However, theses approaches are very different, depend a lot from the culture of the variety of professionals that can take care of these difficulties. We did not find a synthetic description of this diversity in Europe. Conducting a European online survey, taking advantage of European networks like EFPT (European Federation of Psychiatric Trainees), ESCAP (European Society of Child and Adolescent psychiatry) could allow to have a better overview about: (1) the diversity of tools to diagnose, (2) and to rehabilitate dysgraphia, (3) the professionals involved, (4) the economical consequences on the families, (5) the acceptability of using new technologies. We began to implement such survey but proofreading and a pilot phase would be necessary before dissemination.

7.2 Generalisability

Future researches will need to take into account some precautions concerning the data collection and the interpretation of the data. In this thesis, we focused mainly on handwriting features. The features extracted strongly depend on the device used to record them (sampling frequency, resolution) and the software used to extract them. We had such issues and we were not able to directly used the features presented in chapter 3 and 4 in the clinical part chapter 5, even if we used the same hardware, because of a different sampling method with a different software (event time stamps or periodic sampling). Other devices that may be cheaper or easier to use will require to train new models on these new features. Beyond handwriting features directly, we showed that it was possible to track posture with simple devices like a camera and complex deep learning algorithms like Openpose [64] or a more complex device like a kinect and a more easily interpetable random forest algorithm[1]. In this case there is still an open question between the trade-off of accessibility of the device (RGB, very accessible or RGB-D, less accessible) or algorithm (implemented random forest or Deep learning complex algorithm) to disseminate more largely this approach.

7.3 Mystification and ethical aspects

The protégé effect is working in this scenario because the child believe that the robot needs him/her to improve its writing. This does not really make sense in an implementation level since the quality of writing is only a given parameter to the robot controlled by the experimenter. Still, this mystification was good enough to initiate a therapeutic child-robot interaction even if this mystification was not sustained, since the child reported "It's not the robot who learns, it is me". Fortunati et al, showed how children had high expectations toward robots shaped by media, even if the human-like features of fictional robots are more advanced than those reachable by the factual ones [126]. A lot of experimental psychology showed the biases we have as humans [18, 249] and how we are prone to mystification and rationalization [32, 135]. This was also done with a human instead of the robot. In experiments with cyranoïds, people are fooled by a senior experimenter secretly "tele-operating" a child via earphones. People interacting with the child often do not understand that there is an incompatibility between the body and the cognitive

[1] https://www.fondationorange.com/Pictogram-room

function of an individual even with this large difference of age [253]. This question was also raised in the Turing test [328] that tries to provide a method to assess "whether or not a machine can think". If a subject can not distinguish between an interaction with a human and a machine, he assumes that the machine thinks. To explore further these false attributions, we defend that in such an interaction, instead of a binary question ("is this mind-body conjunction possible ?" or "is this machine intelligent"), we could investigate the belief projected by the child on the robot. Thus, we began to investigate such beliefs during journée des classes (schools days) in EPFL university in a group of 61 children during one day. Classrooms were invited in EPFL university to interact with different experiments developped by researchers. Children were able to interact with the co-writer exercices (only the turn-taking writing activity in this scenario) and then rate their perception and inference about the ability of the robot on a Likert scale. We propose several dimensions that could be evaluated: (1) a simple perception dimension describing abilities performed actually by the robot, e.g. the robot is speaking, is moving, is progressing, (2) inferences induced by the scenario, e.g. the robot is progressing, the robots learn to write, the robot has difficulties to write, (3) arbitrary references, e.g. the robot is happy with the relation with the child the robot is nice, the robot is a boy, the robot is annoying, the robot thinks I improved, (4) perception of the autonomy of the robot, e.g. the robot is controlled by a human, the robot is living, a human controls the robot, a human programmed the robot. This day showed the feasibility of this kind of study. It could allow to discriminate between different scenarios.

7.4 E-mental health

Perspectives in the use of technologies in psychiatry

In the introduction, we showed that e-learning could help to improve training in Child and Adolescent Psychiatry (CAP). In this thesis, we showed (1) how we could use algorithms and electronic sensors to characterise the motor difficulties of autistic children, (2) how algorithms and robotics allow to characterise and remediate handwriting.

Above and beyond motor difficulties, use of these technologies is allowing the emergence of a new clinical research field, e-mental health. Psychiatry care is a big challenge since brain disorders cost 800 billion € in Europe, yearly [156]. Depression alone is the leading cause of disability in the world, all healthcare included, according the World Health Organization[2]. Overall, more than 50% of the general population in middle- and high-income countries will suffer from at least one mental disorder at some point in their lives [77, 359]. Some therapies are evidence-based and cost-effective [216]. However, the treatment gap (the mismatch between needs and resources) for people with mental disorders exceeds 50% in every country in the world, approaching astonishingly high rates of 90% in the least resourced countries, even for serious mental disorders associated with significant role impair-

[2]https://www.who.int/news-room/fact-sheets/detail/depression

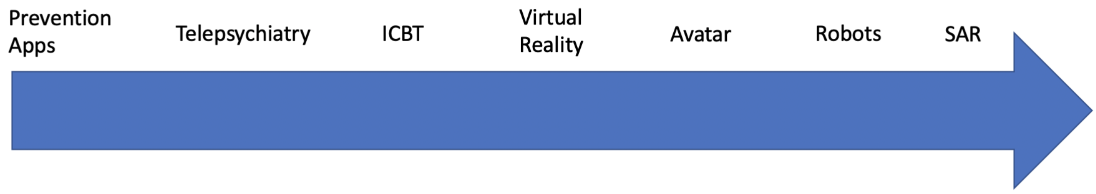

Figure 7.1: Several E-mental health strategies with increasing hardware complexity and professional investment. ICBT: Internet-based Cognitive Behavioural Therapy, SAR: Social Assistive Robotics

ments [288, 327]. Prevention in mental health is critical, yet its implementation is still very low. It would be particularly critical during sensitive developmental periods [17]. E-mental health approaches could help (1) to decrease the treatment gap, (2) to support prevention, (3) to better understand the optimal care.

Here, we will describe several strategies with increasing hardware complexity and professional investment.

Meta-analyses based on randomised trials clearly indicate that therapist-guided stand-alone application can result in meaningful benefits for a range of indications. The clinical significance of results of purely self-guided interventions is for many disorders less clear [111]. Some very well studied psychotherapeutical principles can be applied with apps: mindfulness in used for depression [213][3], exposition and response prevention for Obsessive Compulsive Disorders (OCD) [201]. Serious games were developed as accessible proxy of evidence-based therapies in ASD [193]. Other serious games are tested for visuo-spatials tasks like Tetris® to prevent [185][4] and treat flashbacks after a trauma [54], arcade games in ADHD [209], role play and simulation games for psychoeducation[5]. Chatbots is another strategy that was used in depression and anxiety[6]. Remote consultation (telepsychiatry) deployed rapidly in the context of COVID crisis. Social medias can be used to help patients share their experience together and empower them [267]. In systematic reviews, most controlled studies reported no statistical differences between videoconferencing and in-person psychotherapy in depression [35]. Several meta-analysis [8] and non-inferiority trials [9, 375] showed that Internet Cognitive Behavioural Therapy (online exercises programmed by a therapist) was efficient or even as efficient as face-to-face Cognitive Behavioural Therapy. Systematic reviews showed no evidence that Virtual Reality (VR) is significantly less efficacious than in-vivo exposure in specific phobia like agoraphobia [377]. A preliminary study used VR to allow sensory integration treatment in ASD [194]. Avatars show promising results in the treatment of hallucinations in schizophrenia [86]. These technologies are more mature than robots, especially Social Assistive Robots (SAR) that are presented in this thesis. Virtual agents could be promising in early stage since, it seems to elicit, in some cases, more easily self-disclosure in social anxious interactants since participants are not expected to be judged [197].

[3] e.g. https://www.headspace.com/
[4] https://devpost.com/software/proto-trauma-prevent
[5] https://www.sparx.org.nz/ [243]
[6] https://www.facebook.com/owlielechatbot/

Future research will need to assess better acceptability and training of the professionals to critically use these technologies from apps to SAR. One needs to assess feasibility of technical promises, implementation in a larger scale, responsibility concerning both the potential inefficacy or side effects that could occur using these technologies, especially if human presence is quite far, for instance with apps. How to fund or even reimburse[7] new treatments based on Information Communication Technologies? Developing specific and convincing methods of validation is difficult since the design of these technologies is often iterative and user-centred and the classical one-shot randomised Control trial, which is the gold standard method of evaluation in medicine, does not fit well with this approach.

In the other side, some authors raised concern about the over presence of screens and their negative impact on development, especially language disorders [80]. When controlling for confusing factors, larger studies do not show this large detrimental effect and conclude that this effect is "too small to warrant policy change" [230, 273]. However, the usage can be very different, future researches, would need to distinguish different uses of these technologies. Some activities with screen like educational content or co-view with the parent is positive like [231]. It would allow to better understand the advantages and negative effect of these technologies.

7.5 A better understanding of ASD

7.5.1 An opportunity for the development of biomarkers

Electronic-based assessment of movement difficulties could lead to the development of bio-markers [388]. This would complement the classical questionnaire-based clinical evaluation, first steps for the application of precision medicine in autism [40]. It could then help to guide rehabilitation thanks to tailored automatic feedback loops. Eye-tracking [128, 283] and event-related pupil dilation [4] in social orientation tasks are promising and affordable methods. Scaling-up those methods, thanks to widespread and affordable devices like smartphones could lead to a better understanding of ASD physiopathology and allow screening of ASD in the long term [112].

7.5.2 Sensorimotor difficulties in ASD, the foundation for other difficulties

Many cognitive theories have been suggested to underlie the behavioural and developmental manifestations of autism. Evidence suggests that individuals with ASD are slower to process information at a global level, particularly, when a concurrent local information is present [120, 344]. However, the prominence and the consensus on the potential explanatory value of these cognitive theories "have declined in the past decade" [227] mainly due to the lack of longitudinal developmental studies to support them [120, 227] and to distinguish causal mechanisms and compensatory strategies developed by the child.

On the other side, a developmental sensorimotor approach could be useful. A fundamental approach from cognitive sciences defends that one need to integrate the

[7] https://www.kalb.com/2020/06/16/fda-approves-video-game-for-treating-adhd-in-kids-2/

sensory and the motor systems in a integrated loop, each refining the other, thanks to internal model [383].

Sensorial difficulties are frequent in autistic persons [218, 390]. Higher intensities of sensory issues were associated with more prominent social difficulties and lower adaptive functioning [208]. In the same way, impaired praxis (that included gestures to command, imitation, and tool-use in children) is strongly correlated with the social, communicative, and behavioural impairments that define ASD [110].

The internal models elaborated by the children through sensorimotor contigencies [187] are likely early requirements for the development of higher level function like language, cognitive skills and social skills (Figure 7.3). Impairment of neuronal circuits underpinning sensorimotor functions could trigger an atypical developmental cascade [39, 40]. It is important to have a developmental approach since these processes can improve via compensation mechanism through development.

The social feedback theory states that individuals produce on their face, in a mirror way, the emotions they perceive on the face of other individuals [79, 268]. This fine sensorimotor reaction to social scenes could be an early development step required for early acquisition of social competences. When altering this sensorimotor feedback, it was shown that one can disrupts visual discrimination of facial expressions [268, 384].

Helt et al., found a strong relationship between the restricted replication of emotions in individuals with ASD, and the insensitivity to facial feedback [166]. Trevisan showed in a meta-analysis that the production of facial expressions was impaired in autism (moderate effect size). Facial expressions of individuals with ASD are less frequent and shorter. They are less likely to share facial expressions with others or automatically mimic the expressions of real faces or pictures with faces stimuli [361].

Repetitive behaviours are the only motor symptomatology included in the current diagnostic criteria of the *Diagnostic and Statistical Manual of Mental Disorders*, fifth edition (DSM-5) [22] and in the *International Classification of Diseases*, 11^{th} edition [275] (Chapter 1). Here, we propose, based on this sensorimotor perspective, that social difficulties are only the consequences of sensorimotor issues. Early detection and rehabilitation of the sensorimotor impairment could prevent the entry in the beginning of this developmental cascade. It would limit the consequent difficulties of social cognition, themselves leading to difficult socialization (Figure 7.2).

7.5.3 Computational psychiatry as a way to modelize these sensorimotor difficulties

Computational methods offer opportunities to characterize social difficulties in ASD, with tools like synchrony, imitation measure, interpersonal distance (Chapter 2). However, they allow also to characterize and simulate internal functionning in autism.

The goal of computational psychiatry is to describe and modelize with algorithms these difficulties in mental disorders. It is a recent field with still quite heteregeneous findings. [30, 175].

Pellicano proposed that autistic individuals perceived the world too realistically and rely less on their internal models. Thus, this could lead to sensory overload

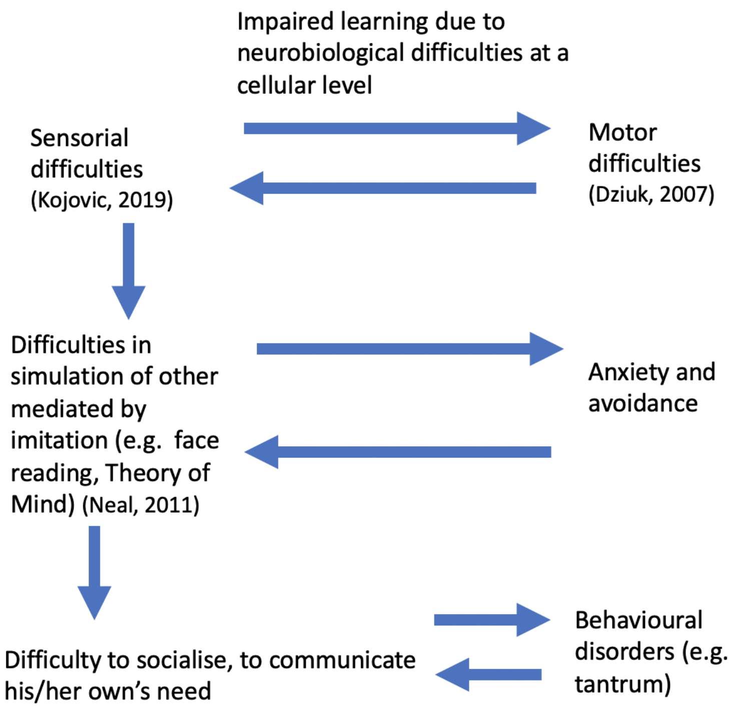

Figure 7.2: Cascade model connecting sensorimotor difficulties to social cognition difficulties and socialisation difficulties in ASD (inspired by [39])

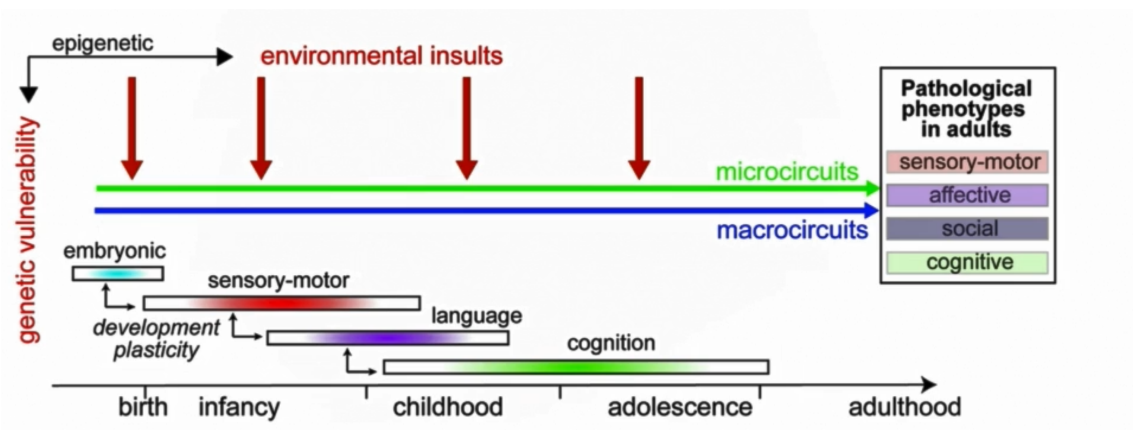

Figure 7.3: Different developmental steps, adapted from [349]

[289]. Using the bayesian decision theory, they suggest that these children have hypo priors, they perceive the world more accurately rather than modulated by previous experience. They over-rely on bottom-up sensory evidence [289]. Lawson used a decision task to assess the learning process in ASD. They showed that adults with autism overestimate the volatility of the sensory environment, i.e., the behavioural and pupillometric measurements showed that adults with ASD were less surprised than controls when their expectations were violated. Instead of focusing on their inner model of the task, they over-rely on the sensory input [215]. This confirm the previous physiological findings, describing different processing of stimuli change [139, 332] and the activation of autonomic nervous system [29].

The embodiement of a humanoid robot dealing with ecological tasks like a ball interaction with a human experimenter allow to model this sensorimotor difficuties at a controllable computational level. Idei et al., used a humanoid robot (Nao) controlled by a neural network using a precision-weighted prediction error minimization mechanism, to simulate computationally the motor disturbance of ASD. They showed that both increase and decreased sensory precision could induce the behavioural rigidity characterized by resistance to change characteristic of autistic behavior [178]. In an other experiment, they simulated changes in intrinsic neuronal excitability at the neural level. After the training of the algorithm, it induced hyper sensory precision and overfitting to sensory noise. These changes led to multifaceted alterations at the behavioral level, such as inflexibility, reduced generalization, and motor clumsiness [179].

7.5.4 Toward new therapeutic strategies focusing on the rehabilitation of sensorimotor difficulties

However, the development is not a simple process since critical windows of development exist, meaning that a function needs sometimes to be developed during a certain period and can not be developed later on due to a reduced plasticity [51,168]. Thus, it could be important to propose early remediation respecting the development of the child.

Virtual reality offers the opportunity (1) to control and reproduce the stimuli presented to the children and (2) to offer a realistic stimulation that mimics an ecological situation (Figure 7.4 A). A sensory overload can trigger behavioural disorders in children with ASD, like tantrums, avoidance, etc. This could improve the understanding of the therapist, the child and his/her family on the way they process these sensory inputs and help them to cope and to habituate [147] to these situations.

Since grasping and upper arm mouvements are one of the first acquired set of mouvements, its study with tangible robots, like Cellulo (Figure 7.4 B), could allow to confirm strategies based on sensorimotor rehabilitation that could prevent to initiate an impaired developmental cascade[8].

A better understanding of these connections could: (1) allow preliminary screening with new biomarkers before the evaluation of higher level functioning like the social skills, (2) improve our understanding of the development of ASD with computanional models, (3) help us imagine management strategies of these sensorimotor

[8]https://ecnp33-ecnp.ipostersessions.com/Default.aspx?s=1B-AB-90-D2-C6-B9-B3-3C-45-AF-18-21-1C-90-E7-7D

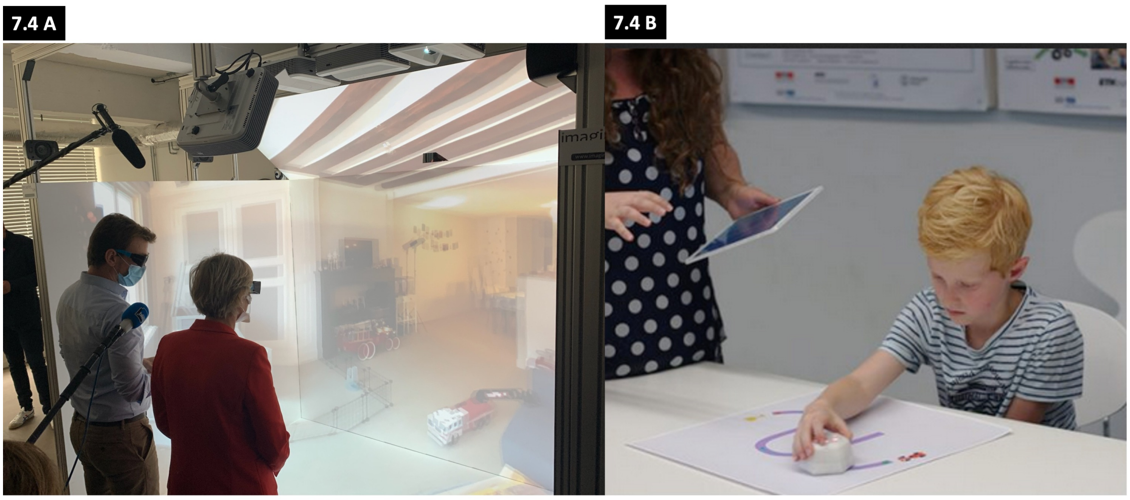

Figure 7.4: Two sensorimotor rehabilitation strategies using information technologies. A: Cube Virtual Reality system to habituate to sensory stimulation, B: Cellulo robot, developped in EPFL, to evaluate and train sensorimotor difficulties of upper arm

anomalies that could be early remediated before the florishing of later social difficulties that are at the moment used for diagnosis (Figure 7.2).

7.6 Follow-up of the project

The coWriter project was funded by a common grant, under the name Irecheck, from the Agence Nationale de la Recherche (ANR) in France and Fond National Suisse (FNS) in Switzerland: to (1) scale up the prototype allow studies with a larger size and (2) to study long-term child-robot interaction in this set up.

7.6.1 Mercator funding for a serious game

The electronic sensors used in the first prototype was a Wacom. This limits the size of the data collection of the system since it needed to be connected to laptop. A new version of the software funded by Mercator Switzerland fundation will be based on iPad (Figure 7.5[9]), a stand alone tablet more available on the consumer market, that will allow to scale up this system.

The iPad are easier to use and allow to display real-time stimuli to perform real time feedback. However, the contact between a glass and the pen is different from the one between paper and a pen [5]. Two strategies would be possible: (1) to consider that the transfer of the motor abilities of children is trivial from glass to paper, (2) to use other system that allow to stick a material on the surface that can keep the feeling and resistance [10].

[9] https://www.dynamico.ch/
[10] doodroo for iPad - The Real PaperFeeling screen protector, https://www.doodroo.com/

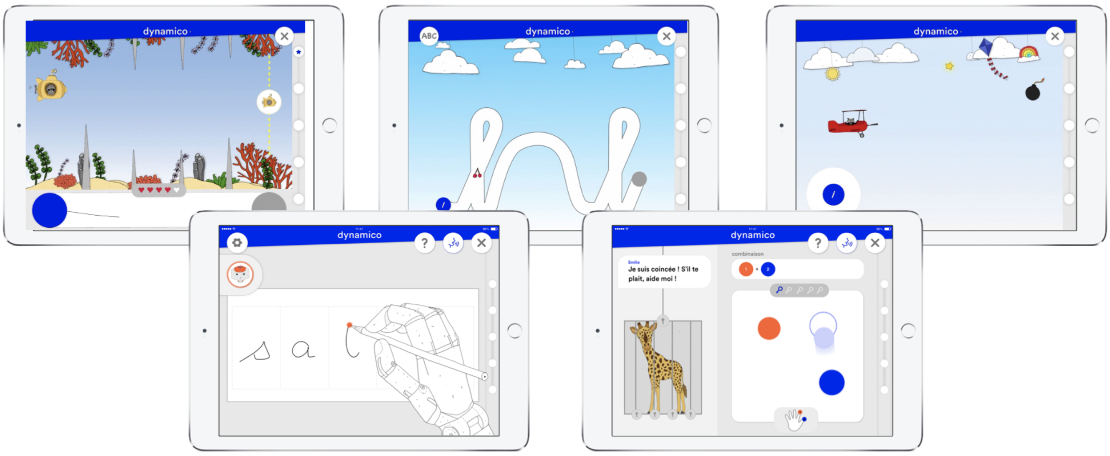

Figure 7.5: Screenshots of Dynamico exercices (from top left to bottom right), adapted games from chapter 5: pressure training game, tracking game, tilt training game, cowriter game and a new game: grasping game.

The goal of this project is to develop a scalable system able (1) to screen and help the diagnosis of dysgraphia, (2) to better understand the place of this approach between normal education, specialised care. A better understanding of handwriting development would allow also to better understand which kind of children would benefit from a rehabilitation, maybe some children would benefit mostly from an adaptation of their environment. (3) to propose tailored adaptative activities to rehabilitate handwriting, to better understand the rhythm of therapy considering the debate between bottom-up and top-down approaches, (3) to validate the efficacy and cost-efficacy of this approach compared with treatment at usual.

The importance of multisensory feedback should also be tested (sound and visual feedback associated). Such tablets will be used with or without a robot and this will allow to study the specific role of the robot. If the robot is important, we will learn until when it is necessary during rehabilitation.

7.6.2 ANR-FNS funding for a social robot

Beyond the question of the embodiement, the iReCheck project[11] will benefit from an other robot Qt Robot which is more stable than a Nao robot and able to display emotions to sustain engagement with the children [150](Figure 7.6).

A new question is the usability of the system and how different populations will take charge of it. Standardised scales could help to measure it [50]. Specialist in writing rehabilitation (psychomotricians and occupational therapists) reported us to want to control as much as possible the wizard of Oz system whereas teachers with which we did some class sessions in schools want the system to be more autonomous to enable a child with specific needs to work alone on handwriting activities meanwhile they can focus on other activities with the other children. Some questions appear, how to handle turn taking activities between several children in class, how to make the robot more aware of the environment to react accordingly (suggest

[11] https://irecheck.github.io/

Figure 7.6: Implementation of the wizard of Oz scenario on a QT robot. See a video demonstration of the implementation: https://youtu.be/hHuEMFIXCEo

behaviours–like the SPARC framework [333]), how the robot is accepted in class and how children accept it, what are the beliefs about its abilities and limitations, compare the practice, funding and acceptability of using new technologies in different contexts. This long-term child-robot interaction in a medical context could allow to better characterize the behaviour of the children and how to adapt the behaviour of the robot [69] thanks to social computing tools assessing non-verbal behaviours that we described in Chapter 1 but also verbal behaviours [324, 373] and their interaction together [372], particularly interesting in ASD since their difficulty to detect irony is well described [101], where irony "can be considered a case of emergence where, e.g., the verbal and non-verbal components of a message are opposite to one another". [372]

Chapter 8

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