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RESEARCH ARTICLE

Using Screen-Based Technologies to Assess Handwriting in Children: A Preliminary Study Choosing Human–Machine Interaction

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ABSTRACT The acquisition of a fluid and legible handwriting in elementary school has a positive impact on multiple skills (e.g., reading, memory, and learning of novel information). In recent years, the growing percentages of children that encounter mild to severe difficulties in the acquisition of grapho-motor parameters (GMPs) has highlighted the importance of timely and reliable assessments. Unfortunately, currently available tests relying on pen and paper and human-based coding (HBC) require extensive coding time, and provide little or no information on motor processes enacted during handwriting. To overcome these limitations, this work presents a novel screen-based platform for Grapho-motor Handwriting Evaluation & Exercise (GHEE). It was designed to support both fully automatic machine-based coding (MBC) of quantitative GMPs and human-machine interaction coding (MBC+HBC) of GMPs accounting for qualitative aspects of a child's personal handwriting style (i.e., qualitative GMPs). Our main goal was to test: the GHEE coding approach in a relevant environment to assess its reliability compared to HBC; the efficacy of human-machine interaction in supporting coding of qualitative GMPs; and the possibility to provide data on kinematic aspects of handwriting. The preliminary results on 10 elementary school children showed reliability of fully automatic MBC of quantitative GMPs with respect to traditional HBC, a higher resolution of mixed human-machine interaction systems in assessing qualitative GMPs, and suitability of this technology in providing new information on handwriting kinematics.

INDEX TERMS Children, grapho-motor skills, handwriting, human–machine interaction, kinematics, machine-based coding, screen-based technology.

I. INTRODUCTION

Handwriting is an essential component of educational curricula in many countries. Research literature shows that the benefits of handwriting extend well beyond its immediate communicative function. Multiple studies comparing handwriting and typing have shown positive effects of the former on reading, spelling, letter recognition, and memory in children [1], [2], [3], [4]. However, mastering the complex grapho-motor skills involved in handwriting is a demanding task, requiring consistent time and exercise. Elementary school children dedicate over 50% of their time to the

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acquisition of fluid movements supporting handwriting [5], [6]. Data from multiple countries show that children often struggle to achieve the grapho-motor competencies required to produce legible handwriting [7], [8], [9], [10]. Recent concerns raised on the growing percentages of children that manifest mild (poor writers) to severe (dysgraphic) difficulties in handwriting, have led both Governments and Academia to suggest the development of more timely and wide-spread assessment tools [11], [12].

A. TRADITIONAL PEN AND PAPER ASSESSMENT TOOLS

To date, the detection of handwriting difficulties in most countries begins with elementary school teachers' reports based on observation of children's performance. Parents may then seek to obtain clinical evaluation at local clinical centers, where grapho-motor skills are measured relying on school notebooks or gold-standard tests for grapho-motor skills. The latter are mostly pen and paper tests providing post-hoc analytic evaluations of the readability of a child's handwriting (evaluating the handwriting *product*), rather than the fine- and gross-motor skills involved during handwriting tasks (measuring handwriting *processes*; e.g., fluid fine-motor planning involved in letter tracing, as well as child posture and/or pen grasps) [5]. For example, in Italy the two most commonly used tests for standardized assessments of children's grapho-motor skills are: the Italian *Test per la Valutazione delle Difficolta' Grafo-Motorie e Posturali della Scrittura* (DGM-P) [13] and the Italian standardization of the *Concise Assessment Scale for Children's Handwriting* (*Brave Handwriting Kinder*) (BHK) [14]. Both tools ask children to use a ballpoint pen to copy one or more typed phrases in cursive handwriting on a sheet of paper. Handwriting is later scored by a human coder (human-based coding, HBC) to measure grapho-motor parameters (GMPs) of relevance (e.g., letter size, word alignment, space between words, margin alignment, etc.). These tests differ in number/types of GMPs and in how they are measured (e.g., the BHK test considers 13 GMPs while the DGM-P measures 12 GMPs with significant differences in scoring methods). Such post-hoc analytic evaluations rely on very fine-grained measurements of GMPs. For example, human coders must actively check for interruptions in the writing trace in order to account for presence of inappropriate connections between letters, and/or measure each letter's height using transparent tracing paper to evaluate appropriate letter size [13], [14]. HBC of some GMPs (e.g., wrong connections between letters) is important as it allows coders to grasp *qualitative* aspects of a child's personal handwriting style, essential in designing tailored exercises. On the other hand, analytic evaluations of other GMPs (e.g., measuring letter size) are purely *quantitative* and extremely time-consuming when relying on HBC. Finally, it is important to stress that post-hoc assessments of the handwriting product provide little or no direct information on the actual processes enacted by children during handwriting. Therefore, intervention strategies rarely target specific motor difficulties experienced by children [5].

Summing up, currently available pen and paper tools for grapho-motor skill evaluation, based entirely on HBC, while very helpful in capturing qualitative aspects of children's handwriting, are extremely time-consuming when considering quantitative measures. This has a negative impact on frequency of child evaluations, especially in public health care centers, which operate under consistent time and cost constraints, with cascading effects on timeliness of intervention.

B. NOVEL SCREEN-BASED TECHNOLOGIES

A viable alternative to traditional pen and paper assessment tools is relying on novel screen-based technologies for child handwriting assessments. These technologies promise to reduce coding times of quantitative GMPs by relying on machine-based coding (MBC) and support the acquisition of kinematic data related to handwriting processes [5]. However, to date, use of screen-based technologies for child handwriting evaluation is limited by: (1) lack of data on reliability of MBC of quantitative GMPs compared to HBC; (2) a wide-spread tendency to develop tools that provide fully automated MBC of all GMPs, and that therefore *replace*, rather than *support,* HBC of qualitative GMPs.

The first limitation is due to the lack of published data on direct comparisons between MBC and HBC of quantitative GMPs (e.g., letter size). As for the second limitation, consistent research has been dedicated to developing tools that allow fully automatic extraction of GMPs, often resulting in systems that only provide, as output measures, composite scores, but little or no information on qualitative GMPs or individual characteristics of a child's handwriting [15], [16], [17], [18]. A less commonly used approach is to rely on 'mixed systems', involving some form of human-machine interaction, to support rather than substitute human coder observation skills [19]. For example, Dimauro and colleagues proposed a software system for early diagnosis of dysgraphia (TestGraphia), allowing fully automatic extraction of some GMPs (which prove to be time consuming when coded exclusively via HBC, e.g., writing size, margin alignment, space between words), while other GMP's were set to be coded by the clinician (e.g., atypical letters, ambiguous letters) [20].

Mixed systems relying on MBC as well as on some human-machine interaction (i.e., MBC+HBC) carry multiple benefits by consistently reducing coding times of quantitative GMPs, while still allowing to grasp qualitative GMPs related to child's personal handwriting style (e.g., atypical connections between letters). However, mixed systems are either rare or still relying on pen and paper data acquisition (as in the case of TestGraphia), therefore providing little or no information on handwriting *processes* [20].

C. WORK OBJECTIVES

In the present study we attempt to overcome the afore-mentioned limitations by modifying a recently developed platform called *Grapho-motor Handwriting*

Evaluation & Exercise (GHEE) to evaluate children's cursive handwriting skills [21]. GHEE was designed to rely on screen-based tools and modified in this study to support a mixed coding approach of GMPs derived from the DGM-P and BHK tests. In preliminary testing with adults, we verified system portability and parsed out those GMPs which would be best coded through MBC or by human-machine interaction [21]. In this paper, we aim to move one step further, testing the GHEE platform to assess GMPs in a group of 10 children and showing:

1. reliability of GHEE MBC of quantitative GMPs compared to HBC of the same screen-based data;
2. efficacy of mixed approaches relying on human-machine interaction when assessing qualitative GMPs;
3. viability of kinematic parameter extraction to extend child handwriting assessments by considering handwriting processes.

In relation to our first objective, in the present work we specifically compared fully automatic MBC vs. the HBC of 4 quantitative GMPs based on children's texts written on the GHEE screen. As for the second aim, we compared the HBC of 2 qualitative GMPs vs. the assessment obtained by the mixed human-machine interaction approach i.e., MBC+HBC). Finally, for the third aim we implemented a measure of fluency based on the analysis of handwriting velocity and tested it simulating different velocity profiles corresponding to different handwriting performances.

II. MATERIALS AND METHODS

GHEE is composed of a Wacom Cintiq 16 interactive display (Display Full HD with a resolution of 1920 × 1080 pixels), a smart pen, the Pro Pen 2 stylus, FIGURE 1.A (see [21] for more details about requirements), and a remote laptop running software for stimuli presentation, data acquisition and GMP extraction. In particular, stimuli presentation and acquisition of pen tip position data have been managed using Eye and Pen Software [22]. Pen tip position data are referred to a global reference frame (Sheet reference frame) centered in the bottom left corner of the screen, with the x axis pointing right and the y axis pointing up. Single words are automatically separated within Eye and Pen, and manually labelled. These data feed a custom App developed in MATLAB R2021a App Designer to perform GMP extraction. This is composed of two modules: i) letter segmentation, performed manually by a human coder; and ii) a coding module performed by GHEE automatically or in collaboration with a human coder. This latter module allows both MBC of quantitative GMPs and/or mixed coding (MBC+HBC) of qualitative GMPs from raw pen data as well as to dynamically interact with the child's written text on the screen by zooming in and/or zooming out.

A. PARTICIPANTS AND PROCEDURES

Ten children (2 males) were enrolled in this study. Inclusion criteria were chronological age between 7 and 9 years, current enrollment in a primary school and exclusion criterion was

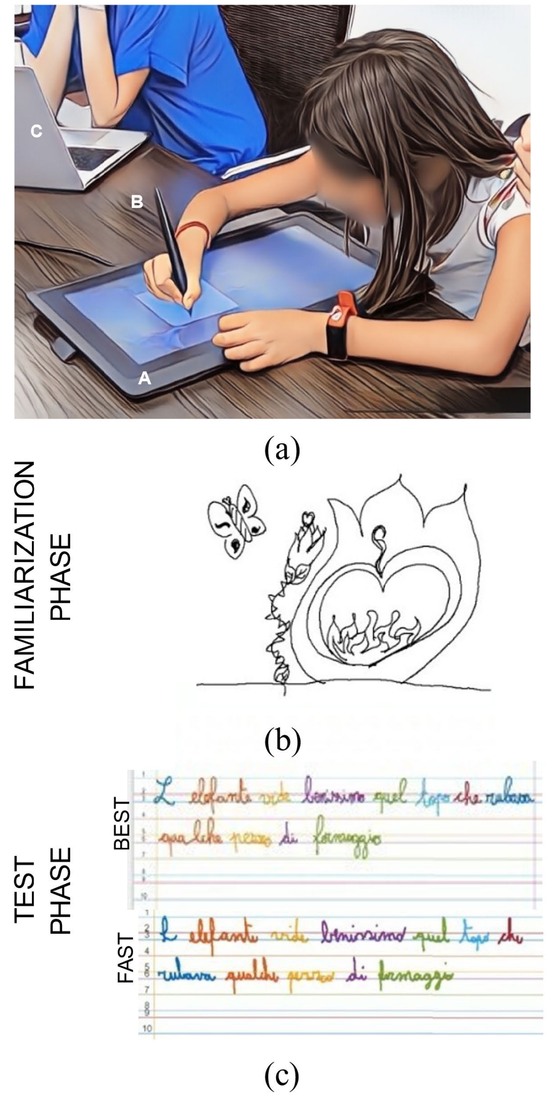

FIGURE 1. Experimental Set-up with the main components of the GHEE platform: Wacom Cintiq 16 interactive display (A); the Pro Pen 2 stylus (B); the remote Laptop (C). In the central and bottom panel of the figure two screenshot of the familiarization phase and of the test phase respectively.

documented history of neurodevelopmental or motor disorders. Based on these criteria, all children were included in the present sample. Participants' mean chronological age was 8.7 years (SD = 0.4, range 8.1 – 9.4 years), they were all right-handed, and had normal or corrected vision, with one participant wearing glasses. Eight children were enrolled in 3rd grade elementary school at the time of assessment, while the remaining two were enrolled in 2nd grade. Intellectual functioning (IQ) was evaluated in all children using Raven's Colored Progressive Matrices (RCPM) [23] and visuo-motor coordination skills were assessed using the Beery Visual Motor Integration Test (VMI), including the Visual Perception and the Motor Coordination subtests [24]. Participants' mean score in the VMI tests was 105.4 (SD 14.2, range 88-134) while mean score in the Visual Perception subtest was 108.2 (SD 11.8, range 86-126) and 116.3 in the Motor

TABLE 1. Participants characteristics. SD: Standard deviation.

N.	Grade	Gender	Right Handed	Chronological Age		RCPM		VMI Total Standard Score		VMI-Visual Subtest Standard Score		VMI-Motor Subtest Standard Score	
				Mean ± SD	Range	Mean ± SD	Range	Mean ± SD	Range	Mean ± SD	Range	Mean ± SD	Range
10	II-III	8 F 2 M	10	8.7 ± 0.4	8.1-9.4	113 ± 14.2	90-130	105.4 ± 14.2	88-134	108.2 ± 11.8	86-126	116.3 ± 12.6	95-127

Coordination subtest (SD 12.6, range 95-127) (see Table 1). All participants displayed an IQ of 90 or above (see Table 1 for participants' details). Participants were recruited through word of mouth, and they completed the GHEE task as well as standardized tests during one study session carried out at Università Campus Bio-medico di Roma. Children showed good understanding of verbal instructions. This experimental study was conducted according to Declaration of Helsinki guidelines and approved by the Ethics Committee of Università Campus Bio-Medico di Roma (protocol code PAR 73.21, Rome 28 Sept. 2021).

Parents of all participating children signed written informed consent prior to children's inclusion in the research sample. The interactive display was placed on a desk in front of the child with the screen oriented vertically and the stylus was placed on the right of the display in accordance with hand dominance in the sample (see FIGURE 1.A). All sessions were video recorded to check for correct software functioning as well as inappropriate sitting positions and or pen grasps (which are the object of another study). Each trial started with a familiarization phase, allowing children to use the stylus on the screen in some drawing tasks (FIGURE 1.B). Subsequently, children were asked to select the type of ruled paper that they commonly used for handwriting in school from a set of virtual paper formats shown on the GHEE screen. They were then shown a typed sentence in Italian, right above the selected virtual paper format appearing on the screen, and asked to copy it in cursive handwriting. The chosen sentence (i.e., "*L'elefante vide benissimo quel topo che rubava qualche pezzo di formaggio*", literally "The elephant could see very well the mouse which stole some bits of cheese") was picked as it includes each letter of the Italian alphabet at least once. Children performed this task twice (FIGURE 1.C): in the first condition they were asked to copy the phrase in their best cursive handwriting (best condition), while in the second condition they were asked to write it as fast as possible in cursive handwriting (fast condition). All participants completed both conditions except for one child who did not complete the fast condition.

B. ASSESSMENT OF GMPs USING GHEE GMPs APP

GMPs were measured using an App developed ad-hoc in Matlab App designer for GMP extraction. GHEE data are organized in two modular and hierarchical structures: "Child-Data" and "Task". The first one collects metadata on the experimental session, that is information related to the child (i.e., age on experiment day, gender, class attended) and the experimental setting (i.e., type of sheet chosen, condition). The structure "*Task*" contains data on ruled paper and raw data. It is divided into two sub-structures: "*Paper*" containing data about the size of rows, columns, and margins of the ruled paper chosen by the participant; and "*Sentence*" containing raw data of the stylus (i.e., timestamp, the x y coordinates of the stylus tip, and a field reporting the "*pen in the air*" label when the stylus is not in contact with the screen and up to 5 cm above it) split in one substructure for each word.

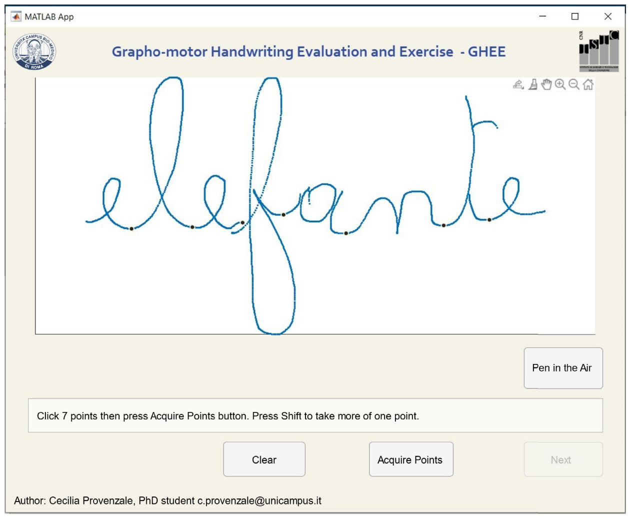

FIGURE 2. **Manual letter segmentation process. The GHEE GMPs detection app asks to the human coder to segment the beginning and the end of each letter.**

The GHEE GMPs App implements the mixed approach described above to extract four quantitative GMPs, two qualitative GMPs, and one GMP directly related to handwriting kinematics. Firstly, it instructs the coder to manually segment the beginning and the end of the written trace for each letter. A dedicated window allows to mark these points with simple mouse clicks (see FIGURE 2). On average, a total of 50 mouse clicks were necessary for the overall sentence segmentation in our sample. Data manually segmented and

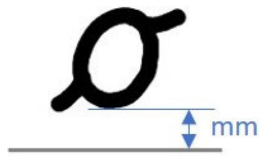

FIGURE 3. Measure of the vertical distance between letter and paper line. The distance is considered positive when the letter is above the line as in figure, negative otherwise.

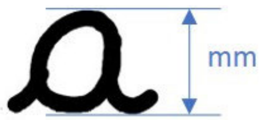

FIGURE 4. Measure of the height of the letter as the distance between the letter extremal points along the vertical axis.

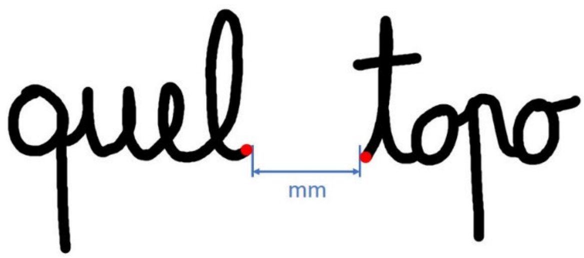

FIGURE 5. Measure of space performed by GHEE GMPs App. Red points represent the extremal points between which the measure is performed, i.e., the last point of the word "quel" and the first point of the following word "topo".

FIGURE 6. Linear fitting of the left extremal points of each line to measure the alignment with the left margin.

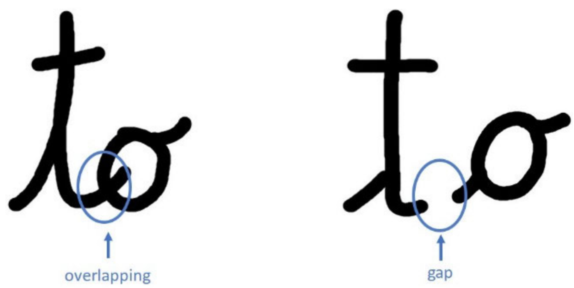

FIGURE 7. Measure of connections performed by GHEE GMPs App. It verifies the presence of an overlapping (example on the left) or a gap between letters greater than 0.5 mm (example on the right).

labelled are subsequently used for automatic coding of GMPs as detailed in the following paragraphs.

Fluctuations which measure the vertical distances between each letter and the paper line (see FIGURE 3), include two features: i) amplitude of fluctuation defined as the sum of the maximum vertical distance in mm above and below the ruled paper line [13]; ii) number of fluctuating letters, computed as the number of letters with a distance above or below the ruled paper line exceeding 1.5 mm [13].

Dimensions which measure the height of each letter (see FIGURE 4) include three features: *i)* height variation of medium letters (HV_{mL}, i.e., a, c, e, i, m, n, o, r, s, u, v, z); *ii)* height variation of ascending/descending letters (HV_{adL}, i.e., b, d, f, g, h, l, p, q, t), both defined as the difference in mm in letter height between the largest and smallest letter within each letter group [13]; *iii)* overall letter height (OH) defined as the average height in mm of the largest and smallest medium letters [14].

Space: space between words, corresponding to the difference between the coordinates of the last point of a word and the first point of the following one, along the horizontal axis (see FIGURE 5). This space is labeled as "insufficient" when it is below a set threshold, defined according to [14] as the mean width of the letter "o" measured for each child. To define this threshold for each participant, GHEE fits the points of each "o" letter with an elliptical law, extracts the measures of the horizontal axes, and sets the threshold as their median value.

Margin alignment which measures the alignment with theleft margin. A linear fitting of the left extremal point of the first letter of each line is computed (see FIGURE 6). The margin alignment is scored as 0 if the angular coefficient is positive, otherwise it is assessed using a set of 5 oblique lines derived from the BHK test [14]. In detail, it is scored between 1 to 5 according to the line with the angular coefficient nearest to the one measured with the linear fitting.

Furthermore, a mixed approach based on human-machine interaction was implemented to extract two qualitative parameters, as follows:

Connections: errors in connecting adjacent letters. GHEE verifies the presence of an overlapping between letters; if it is not present, GHEE measures the lowest Euclidian distance between each couple of consecutive letters and compares it with a threshold set to 0.5 mm (according to the thickness of the digital trace, i.e., 2 pixel) (see FIGURE 7). In case of overlapping, or for distances higher than the threshold, GHEE assesses the connection as "missing or wrong connection" and provides the human coder with a visual outcome of the results asking them to approve or reject the evaluation, thus performing an MBC *supervised* by a human coder (MBC-H). Differently from [21] a mixed approach has been implemented to code this parameter in order to avoid missing out on relevant qualitative information on what type of errors (e.g., missing connection vs. overlapping) are being made by the child and where.

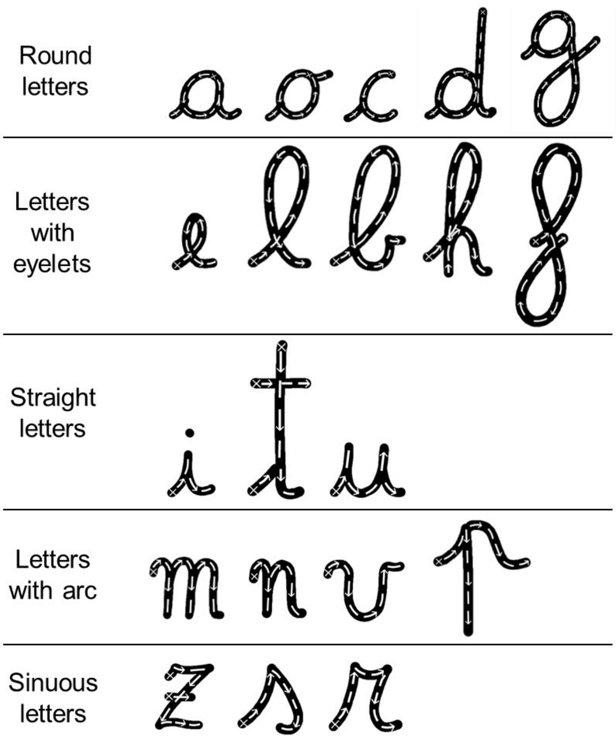

FIGURE 8. Letter directions according to [25]. Letters were grouped in 5 classes according to their morphological characteristics.

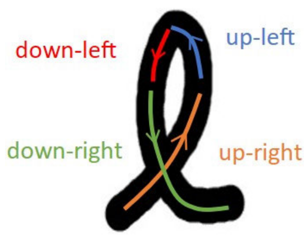

FIGURE 9. Example of the 4 directions assessed by GHEE GMPs detection app.

Direction: sequence of movements with which the child has traced the letters compared to letter tracing directions taught by teachers in elementary school (FIGURE 8). For example, in letters containing round shapes (a, c, d, o, q) children are taught that these should be written using counterclockwise movements, while for letter with eyelets (b, e, l, h, f) children are taught that these should be traced with an initial upward movement followed by a downward one [13], [25]. GHEE identifies 4 main directions by analyzing stylus tip kinematics (see example in FIGURE 9): i) up-right, for an increment along both x and y axes; ii) down-right, for an increment along x axis and a decrement along y axis; iii) up-left, for an increment along y axis and a decrement along x axis; and iv) down-left for a decrement along both x and y axes. The software provides a visual representation of the sequence of directions identified for each letter according to the target movement of the specific class to which the letter appropriateness of letter tracing direction belongs. The coder

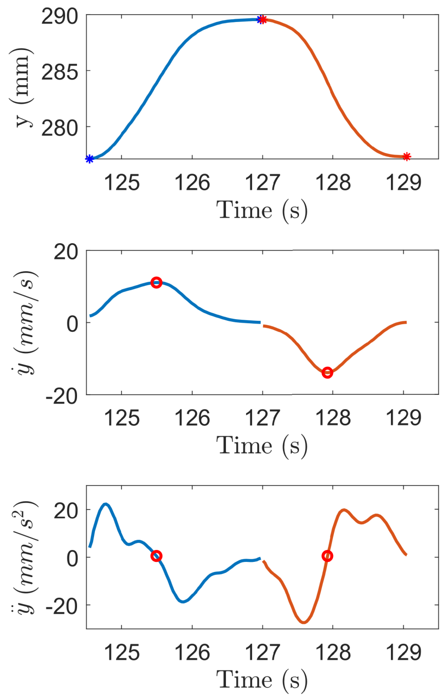

FIGURE 10. Example of NIV extraction derived from the experimental dataset. The upper plot shows the vertical position data with highlighted local extremal points corresponding to a change in vertical direction. These points correspond to 0-points of the vertical shown in the central figure. Local minima and maxima points in the vertical velocity (red circle in the figure) correspond to a change in the sign of the vertical acceleration (0-points of the vertical acceleration), i.e., to a ballistic movement.

is then in charge of assessing, thus performing an "HBC *supported* by the machine" (HBC-M).

Finally, alongside Directions, we attempted to extend current evaluations of handwriting processes in children by measuring a GMP accounting for the fluidity of handwriting movements. To this aim, we focused on the fully automatic MBC of the **Number of Inversions of Velocity (NIV)** [26] [27], [28], which is a measure of the number of directional changes in vertical velocity (i.e., along the y axis of the sheet reference frame). At the base of NIV there is the assumption that a fully developed handwriting process can be considered as a sequence of elementary ballistic movements: i.e., movements composed of a single acceleration followed by a deceleration phase [29].

This assumption, confirmed by [29] and [30], extends the findings of Morasso and colleagues [31], which showed that point to point movements of the arm can be described via bell-shaped velocity profile. According to [32], NIV is measured along the vertical direction (y(t), see FIGURE 10): the sentence is divided into components, i.e., a sequence of characters of the same word between two consecutive pen lifts [16]. Each component is further divided into intervals (called strokes) between two consecutive local extreme points (maxima/minima) of the vertical position coordinate [32], [33]. Within each stroke, y(t) data are filtered for noise reduction using a second order low pass Butterworth filter with cut-off frequency equal to 10 Hz [16]. The vertical velocity is computed by means of a 9-point central difference function [34] and the NIV is measured as the number of local maxima and minima in the vertical velocity, corresponding to a change in the sign of the vertical acceleration (see FIGURE 10) i.e., to a ballistic movement. If only one extremal point is found in the stroke, this means that only one ballistic movement has been carried out with a bell-shaped profile in velocity.

Summing up, in each condition (i.e., best and fast) GHEE's coding of GMPs uses a fully automatic MBC approach for Fluctuations, Dimensions, Space, Margin alignment, and NIV, whereas Connections and Directions are coded using a mixed human-machine interaction approach: MBC-H and HBC-M.

C. ASSESSMENT OF GMPs USING TRADITIONAL HUMAN BASED CODING

An image of the sentence written by each participant was printed on a A4 sheet, with horizontal and vertical resolutions equal to 96 dpi. This resolution was chosen to avoid altering proportions and/or letter size. A human coder assessed each child's handwritten text as printed from the GHEE screen to code qualitative and quantitative GMPs, except for the NIV, which could only be extracted using GHEE. Each dataset was split according to task conditions: best and fast. **Fluctuations**, **Dimensions**and**Space** included quantitative features as in GHEE GMPs App (i.e., amplitude of fluctuation, number of fluctuating letters, height variation of medium letters, height variation of ascending/descending letters, overall height, space between words). These GMPs were measured manually using transparent graph paper with 1 mm resolution and manually calculated using coding criteria described in GHEE's MBC above and coding procedures described in [13] and [14]. **Margin alignment**referred to the same GMP coded in the GHEE GMPs App and was manually scored using a transparent scoring sheet with 5 oblique lines, identical to the one provided in the BHK test [14]. The human coder placed the transparent scoring sheet with the 5 oblique lines on the child's written sample to check for text alignment and used the same scoring system present in GHEE described above. **Connections**and **Directions**were manually coded through post-hoc observation of the child's written trace. Any interruption or overlap in the trace was analyzed and scored as a missing/incorrect connection as in GHEE, while errors in letter tracing direction were inferred from the trace and assessed following the coding procedures described in [13].

D. DATA ANALYSIS

In order to demonstrate reliability of the GHEE platform in a relevant environment with children, and test the effectiveness of the mixed coding approach, we assessed the level of agreement between traditional HBC and GHEE coding both for handwriting product and process.

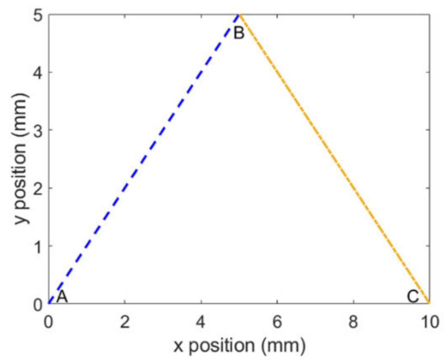

FIGURE 11. **Linear trajectory used to test the algorithm for NIV extraction.**

Normality distribution of GMPs was tested relying on the Shapiro-Wilk test and the comparison between traditional HBC and the outcome of the GHEE GMPs App was performed with a paired samples t-test or with the Wilcoxon signed-rank test, depending on the distribution type (normal vs non-normal distribution respectively). For quantitative parameters, a significant difference between the two datasets means a poor agreement between HBC and MBC.

For the qualitative parameters relying on a mixed coding approach (i.e., Connections and Direction) comparisons between traditional HBC and GHEE GMPs App may justify the use of a mixed MBC+HBC approach.

To test the algorithm for NIV extraction we defined a simple linear trajectory between three points (see FIGURE 11). This trajectory simulated simple point to point movements and allowed to control movement characteristics to simulate different levels of smoothness. The points' position was chosen limiting the vertical displacement to space between paper lines of Italian II grade students' paper notebooks (i.e., 5 mm). The horizontal displacement was chosen arbitrarily, because, NIV measurement relies only on vertical displacement. According to the stroke definition, the trajectory chosen is composed of two strokes: stroke 1 from A to B; stroke 2 from B to C. For each stroke we simulated three fluency conditions: perfect (NIV =1); moderate (NIV = 3, i.e., close to the mean fluency expected for a 4th grade child [26]), and poor (NIV = 15, i.e., 5 times the NIV expected for a 4th grade child and higher than the maximum NIV (i.e., 9) measured in 48 children with handwriting difficulties [26]) by composing quintic polynomial velocities with 1, 3 and 15 local maxima or minima velocities, respectively.

Finally, we measured the time needed for HBC and GHEE GMP extraction in the best trial within the best condition (i.e., the trial with the highest score) and the worst trial within the fast condition (i.e., the trial with the lowest score) in order to compare the two assessments in terms of coding time.

III. RESULTS

Comparison of quantitative GMP coding relying on GHEE's MBC vs. traditional HBC did not show significant differ-

TABLE 2. Comparison between MBC vs. HBC for Fluctuation, Dimension, Space, and Margin GMPs. The values reported in the table represent averages for features analyzed through paired samples t-test while median values for those analyzed through Wilcoxon signed rank test.

GMP	Features	Assessment				Statistics	
		Best cond.		Fast cond.		Best cond.	Fast cond.
		MBC	HBC	MBC	HBC		
Fluctuation	Amplitude fluctuation	2.7 (mm)	2.6 (mm)	4.2 (mm)	3.6 (mm)	t(9) = -0.337 p = 0.744	t(8) = -1.781 p = 0.113
	Number of fluctuating letters	3.5 (a.u.)	3.5 (a.u.)	10 (a.u.)	13 (a.u.)	Z = 21 p = 0.722	Z = 26 p = 0.050*
Dimensions	Height variation of medium letters	3.3 (mm)	3.1 (mm)	3.6 (mm)	3.5 (mm)	t(9) = -1.156 p = 0.278	Z = 11.5 p = 0.213
	Height variation of ascending/ descending letters	4.7 (mm)	4.4 (mm)	5.8 (mm)	5.1 (mm)	t(9) = -1.868 p = 0.095	t(8) = -1.279 p = 0.237
	Overall letter Height	3.7 (mm)	3.8 (mm)	4.5 (mm)	4.3 (mm)	t(9) = 0.814 p = 0.436	t(8) = -0.981 p = 0.355
Space	Space between words	0 (a.u.)	0 (a.u.)	1.8 (a.u.)	1.2 (a.u.)	Z = 4 p = 0.850	t(8) = -1.348 p = 0.214
Margin alignment	Left margin alignment	0 (a.u.)	0 (a.u.)	0 (a.u.)	0 (a.u.)	Z = 0 p = 0.089	Z = 0 p = 0.149

TABLE 3. Comparison between MBC-H and HBC for the connections parameter. Table reports connection errors detected by the human coder (HBC) and by the machine supervised by a human coder (MBC-H) in the two task conditions.

Participant	Best cond.		Fast cond.	
	MBC-H	HBC	MBC-H	HBC
1	8	5	-	-
2	14	8	11	13
3	8	6	7	5
4	14	7	10	9
5	16	7	18	9
6	16	7	23	10
7	17	6	13	7
8	16	8	12	10
9	12	6	7	6
10	11	8	9	7

TABLE 4. Comparison between HBC-M and HBC for the direction parameter. Table reports direction errors detected by the human coder (HBC) by the human supported by the machine (HBC-M) in the two task conditions.

Participant	Best cond.		Fast cond.	
	HBC-M	HBC	HBC-M	HBC
1	2	0	-	-
2	11	1	15	1
3	2	0	3	0
4	1	0	0	0
5	0	0	2	0
6	2	0	7	0
7	2	0	5	0
8	3	4	0	4
9	24	0	18	0
10	0	0	1	1

ences in terms of amplitude fluctuation, height variation of medium letters, height variation of ascending/descending letters, overall letter height, space between words, and left margin alignment in both conditions (i.e., best and fast). Only the difference in number of fluctuating letters (10 vs. 13 respectively in MBC and HBC) showed a weak significant difference and only in the fast condition ($Z = 26$, $p= 0.050$) (see Table 2). Comparison of qualitative GMP coding relying on mixed MBC+HBC approach vs. traditional HBC showed highly significant differences in terms of Connections in both best ($t(9) = -6.771$, $p < 0.001$) and fast ($t(8) = -2.419$, $p = 0.042$) conditions. MBC-H approach detected a higher number of errors in both cases (best condition: 13.2 with GHEE vs. 6.8 with HBC; fast condition: 12.2 with GHEE vs. 8.4 with HBC) (see Table 3). Furthermore, a highly significant difference emerged in Direction, but only in the best condition ($Z = 1.5$, $p = 0.023$). Once again GHEE's mixed system detected a higher number of Direction errors (see Table 4). Finally, FIGURE 12 shows the three conditions simulated to test NIV extraction: the upper part shows the linear trajectory (stroke 1 between points A-B, blue line; stroke 2 between points B-C, orange line); the bottom part displays the vertical velocity profile simulated along the vertical direction. Red circles indicate occurrences of inversions of velocity as detected by GHEE.

The number of inversions fits with the artificial trace generated to test NIV. The comparison of coding times between HBC and GHEE GMP extraction, shows that GHEE allows to save about 8% of coding time as compared to manual coding in the best trial (i.e., 01:22" with GHEE coding vs. 17:48" with manual coding) and 23% of coding time as compared to manual coding in the worst trial (i.e., 05:22" with GHEE coding vs. 23:19" with manual coding).

IV. DISCUSSION

Novel screen-based technologies appear to be promising tools to assess the grapho-motor skills that are needed in order to produce legible and fluid handwriting in childhood. In fact, current standardized tools supporting analytic evaluations of both quantitative and qualitative GMPs rely heavily on HBC, which proves to be particularly time consuming. Furthermore, these tools are mostly post-hoc evaluations of written texts, therefore they shed no light on the kinematics of handwriting processes enacted by children. However, the use of screen-based technologies is currently limited by multiple factors. One first limitation is due to lack of published data on direct comparisons between MBC and HBC of quantitative GMPs.

A. RELIABILITY OF GHEE MBC OF QUANTITATIVE GMPs

In this work we aimed to address lack of published data on direct comparisons between MBC and HBC of quantitative GMPs by proposing a novel screen-based system, the GHEE platform, which allows for automatic coding of 4 quantitative GMPs and compared its performance with traditional HBC. For this reason, even if GHEE aims at supporting the work of coders allowing to save some coding time (as detailed above), we preferred to maintain letter segmentation and labelling manual, focusing the reliability assessment only on the automatization of the tasks necessary to code the manually segmented data. This comparison showed that GHEE is able to automatically code all quantitative GMPs with an accuracy equivalent to the one obtained via traditional HBC when children are asked to copy a phrase in cursive handwriting as best they can. On the other hand, when they are asked to copy it as fast as they can GHEE was able to reliably code 6 out of the 7 target features of quantitative GMPs, but some differences emerged in the number of fluctuating letters detected. Since traditional HBC of this GMP requires the alignment of transparent graph paper on the text, such a difference may be due to a parallax error, amplified by the higher number of fluctuating letters in the fast condition. Such interpretation seems to be confirmed by the absence of any difference in the amplitude of fluctuation: indeed, parallax error introduces an offset in the measurement that is compensated in the assessment of the amplitude of fluctuation. Moreover, our data concerning the time that is needed to assess the text with HBC compared to GHEE GMPs extraction in the best and worst trial confirms that GHEE is a time-saving device notwithstanding reliance on manual segmentation. In our future developments of GHEE, we intend to test new forms of automatic letter segmentation to further reduce coding times.

B. EFFICACY OF MIXED APPROACHES

A second limitation toward use of screen-based technologies in child handwriting evaluation is due to the fact that consistent research has been dedicated to developing tools that allow fully automatic extraction of qualitative GMPs, resulting in systems which provide little or no information on individual characteristics of a child's handwriting. To avoid this issue, GHEE was designed instead as a mixed tool supporting some human-machine interaction (MBC+HBC approach). Therefore, our second aim was to test the reliability of this mixed MBC+HBC approach in assessing qualitative GMPs against traditional HBC. GHEE graphically presents connections and directions to the coders asking them to confirm the presence of missing/wrong Connections (i.e., MBC supported by a human, MBC-H) and to assess the appropriateness of the sequence of movements performed to write a specific letter (i.e., Directions) showed on the screen (i.e., HBC supported by the machine, HBC-M). Comparisons with results from traditional HBC and assessment of a copy of the sentence printed on an A4 sheet, showed significant differences in both parameters. In particular, the differences in Connections were significant in both conditions (best and fast), while as for Directions the difference was significant only in the best condition. These differences may possibly be due to a more accurate assessment of qualitative GMPs performed by GHEE. This is supported by the fact that for both Connections and Directions the GHEE's MBC+HBC system allows to detect a greater number of errors in both conditions. Based on our observation of GHEE's coding system we hypothesize that this greater accuracy is due to the fact that GHEE allows the human coder to dynamically interact with the child's written text on the screen by zooming in and/or zooming out. While this result confirms that novel technologies may enhance current assessment procedures for children's grapho-motor skills, by supporting clinicians rather than substituting them, it also raises new and relevant issues in translational terms. For example, given that current standardized assessment tools refer to normative data which are based on pen and paper systems with a different level of accuracy, the application of screen-based systems, implementing an MBC+HBC approach, may risk overestimating handwriting difficulties, as our preliminary data seem to point out. Therefore, an appropriate use of these new technologies will require better comparisons with standardized tests. However, it is important to note that, by allowing coders to directly interact with the text, GHEE may in fact provide clinicians

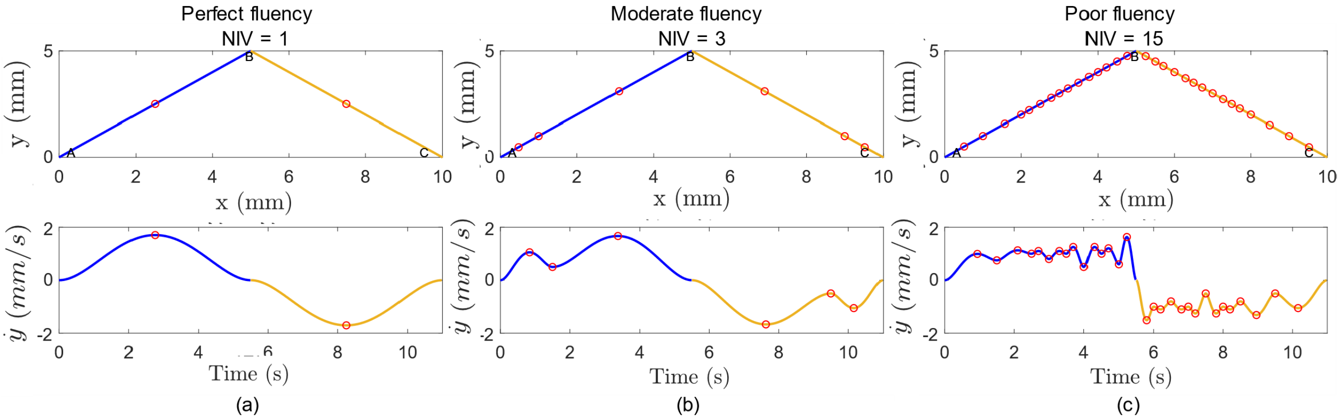

FIGURE 12. Conditions simulated to test NIV extraction. The simulated trajectory reports two point-to-point movements, respectively from A to B and from B to C. Three different conditions have been simulated. In the first column we simulated one ballistic movement corresponding to a maximum and a minimum point in the velocity profile. In the central column we simulated a condition of moderate fluency. Each point to point movement was split into 3 acceleration/deceleration couples corresponding to 3 extremal points in the velocity profile. In the right column we simulated a low fluency, with each point to point movement split in 15 acceleration/deceleration couples. Red dots represent the event automatically identified by the program.

with relevant qualitative information supporting the design of tailored intervention strategies.

C. BENEFIT OF KINEMATIC PARAMETER EXTRACTION

In the present work we aimed to show that screen-based tools may have the benefit of providing some information on the kinematics of the process enacted by children during handwriting. To this scope, we extracted the NIV parameter to measure handwriting fluency. Given that this GMP cannot be assessed via HBC, we proposed a new method to test the reliability of the algorithm implemented for its extraction. We developed synthetic traces at three different levels of NIV and assessed them with our algorithm. Results show the ability of the algorithm to recognize the different simulated levels.

D. ACHIEVEMENTS, LIMITATIONS, AND FUTURE WORKS

This preliminary study on 10 children demonstrates portability and reliability of the GHEE platform's mixed MBC+HBC approach against traditional HBC of GMPs in relevant environment. These preliminary results on a small sample support the use of novel screen-based technologies for handwriting assessment. Our sample size is shared by previous studies addressing similar issues [17], [35], [36], but we still strongly believe that our results may only be considered as preliminary and that further comparisons are needed with standardized pen and paper tools on larger children's groups. Further studies, with larger samples, should also consider the correlations between scores on standardized tests assessing visuo-motor abilities involved in handwriting (e.g., VMI, M-ABC) and GHEE assessments. This is something we are pursuing in our current research. Notwithstanding initial manual segmentation and labelling of letters, the proposed system allows to significantly reduce coding time, while maintaining a good level of reliability. This choice was a limitation of the current system due to the necessity to check for appropriately comparable data. Future endeavors may consider providing effective automatic letter recognition as attempted in other studies [37], [38], [39] to further reduce coding time.

Relying on screen-based technologies to provide new kinematic data which cannot be extracted via traditional HBC (i.e., NIV), also suggests that these technologies may be further exploited to provide data on other motor components of handwriting (e.g., pen pressure, grasps) or to extend the number/type of features considered in the present paper also to younger children. For example, Park and colleagues in [40] used a Novint's Falcon haptic device to investigate the influence of several haptic guidance methods on handwriting skills; Kim et al. in [41] built a workstation to provide force feedback for transferring and improving handwriting skills. In [42], the authors investigated the influence of pen grasp on handwriting speed and legibility asking children to write on a tablet using a pen instrumented with an array of 64 Tekscan 9811 force sensors applied to the pen barrel [43]. Polsley and colleagues in [44] implemented a machine learning algorithm to automatically recognize drawing patterns important for handwriting (i.e., curvature and corner drawings); Serpa-Andrade et al. in [45] used a neural network trained with a collection of images drawn by 300 children to automatically assess prewriting skills of children based on analytical descriptors (moment invariants [46] or on shape signature [47]). These approaches rely on quantitative features based on the assessment of analytical descriptors.

Notwithstanding such promising preliminary results, further analyses are needed to assess the impact of these tools on handwriting assessments. Indeed, multiple studies [15], [48], [49] have shown that different tools influence grapho-motor skills in multiple ways, and that these effects need to be closely monitored especially in children that are still acquiring skilled handwriting.

V. CONCLUSION

This paper aimed at overcoming the limitations currently posed by gold-standardized pen and paper tests for handwriting assessment in childhood. Our goal was to test portability and reliability in relevant environment of a new screen-based platform (i.e., GHEE) implementing a mixed machine and human based coding system (MBC+HBC) to extract grapho-motor parameters (GMPs) which contribute towards text legibility and are, therefore, relevant in handwriting. The work is innovative for several reasons. First of all, it was the first to allow a direct comparison between assessments exclusively based on human coding (i.e., HBC pen and paper assessments) of GMPs and assessments based on a mixed approach (i.e., MBC+HBC), the latter allowing to significantly reduce coding time, while maintaining a good level of reliability notwithstanding initial manual segmentation and labelling. Moreover, we showed how the use of screen-based technologies may potentially extend current assessments of handwriting skills in elementary school children by providing information on kinematics of handwriting processes enacted by children.

In this paper we asked a group of 10 children to copy a sample text in cursive handwriting using a stylus on a screen. Children's texts were then analyzed to extract 7 GMPs of relevance (e.g., including both quantitative and qualitative GMPs) either manually via HBC (with the only exception of NIV) and through MBC or MBC+HBC as implemented in the GHEE platform. This allowed us to achieve the paper's main goals:

1. We confirmed reliability of GHEE's coding of quantitative GMPs given that only minor differences emerged compared to HBC of the same screen-based data;
2. We proved the efficacy of GHEE's mixed approach (MBC+HBC) of qualitative GMPs as GHEE's measurements appeared to be more accurate and we also suggested the necessity to extend data acquisitions with MBC+HBC systems in order to achieve reliability.
3. We showed viability of using GHEE to achieve novel data on the kinematics of handwriting in children by showing the possibility of extracting parameters related to handwriting fluidity (e.g., NIV).

Our findings are of great relevance for research studies addressing the development of novel screen-based technologies to assess handwriting skills in elementary school children. However, our dataset only included 10 participants; therefore, future works should attempt to extend use of a similar technology to larger samples. Another possible limitation of this work is that it only compared different types of coding, while the handwritten texts were all produced on the screen; future works should attempt to compare paper assessments and screen-based assessments to better parse out the impact of screen use and of different writing tools on child handwriting.

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