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Quantitative analysis of the correlation between body posture quality assessment scores and handwriting quality measures

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Various technological applications for body posture correction have been proposed in order to improve handwriting or facilitate its learning for children, under the assumption that a better posture promotes better handwriting. However, very little research investigates the correlation between body posture quality and handwriting quality. Moreover, investigating this correlation typically necessitates the expertise of human observers, leading to high costs, slow progress, and potential subjectivity issues. Consequently, this method may not be suitable for educational environments that require prompt feedback and interventions. In this paper, we present a fully-automated pipeline for the real-time assessment of body posture quality, which builds upon validated scales from ergonomics, which relies on red green blue depth (RGB-D) camera data to compute the rapid entire body assessment (REBA)/rapid upper limb assessment (RULA) body posture scores. Together with a state-of-the-art tool for the automated, real-time assessment of handwriting quality, we applied our pipeline in an experiment at school involving 31 children, to quantitatively and objectively investigate (i) the correlation between body posture quality scores and handwriting quality measures, as well as (ii) the impact that interventions aimed at improving the children's body posture have on their handwriting quality. Our findings (i) demonstrate the correlations between specific postural element quality assessment scores (e.g., neck score) and handwriting dimensions (e.g., static features), and (ii) indicate that interventions aiming to improve body posture quality also have an immediate, significant positive effect on handwriting quality.

Keywords Handwriting training, Handwriting, Body posture, Correlation analysis, REBA/RULA, Child–computer interaction

Handwriting is an important, fundamental, complex skill that takes years to master [1] and has a significant impact on learning, schooling, and communication. It is therefore not surprising, but tragic, that nearly one-third of children between 4 and 12 years are affected by different levels of handwriting difficulties [2].

Recent years saw a rising interest towards the use and development of assistive technologies and software for the purposes of handwriting learning and training. Such efforts include special training support for visually-impaired people with tactile interfaces [3], automated handwriting analysis and exercise games with digital tablets [4], engagement maintenance and confidence restoration with social robots [5], etc.

More specifically, various research works and commercial products focus on promoting a correct body posture during handwriting targeting improvements in handwriting performance and physical well-being. As an example, a dedicated mechanical apparatus was designed for this purpose, envisioning a rigid bracket mounted in front of the desk to physically prevent children from writing in a slouched pose [6]. To tackle the same problem via a different approach, Luo [7] developed intelligent glasses capable of monitoring the face-desk distance and head pose and thereby timely alert the user of any undesirable pose. Similarly, Wu et al. [8] proposed a digital surveillance system with infrared sensors that can be mounted on top of conventional pens as a pen sleeve to detect any incorrect handwriting body posture and remind the children of the wrong posture via a flashlight, beeper and vibrator accordingly. These methods all rely on the same recommended body posture for handwriting [9] as a reference, which is commonly presented in handwriting instructional materials and defined

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as the pose such that the ankle, knee, and hip angles are around 90 degrees with the forearms resting on the desk and feet flat on the floor.

A fundamental assumption of all the aforementioned body posture correction systems for handwriting training is that there exists a correlation between the quality of one's body posture and the quality of their handwriting, which, while is widely accepted, is not yet sustained by conclusive scientific evidence [10,11]. We argue that the body posture and handwriting interplay is crucial for Child-Computer Interaction (CCI) systems that provide handwriting training interventions tailored to specific difficulties and preferences.

Handwriting quality and body posture quality, moreover, are typically assessed by human experts, on the basis of direct observation and reference scales[10–12]. Such assessment methodologies not only suffer from humans' intrinsic subjectivity, but also do not allow for a straightforward automatisation. Recent works have started to focus on semi-automated methods using motion capture systems or multi-camera systems for postural assessment [13,14]. Aiming at endowing a handwriting training system with the ability to assess a child's body posture and handwriting quality in real-time, and intervene appropriately, in this article we propose a pipeline using a single Red Green Blue-Depth (RGB-D) camera for the automated real-time assessment of body posture quality, which computes the Rapid Entire Body Assessment (REBA)[15] and Rapid Upper Limb Assessment (RULA)[16] scores on features extracted from RGB-D images.

Building on our body posture quality assessment pipeline and a recently developed tool for the automated assessment of handwriting quality [4], we then quantitatively investigate the relationship between body posture quality and handwriting quality as shown in Fig. 1. To this end, we designed and conducted an experiment involving 31 children aged 8-9 years old in school.

The objective of this study is to provide: (i) an automated, real-time assessment pipeline of body posture quality using a single RGB-D camera; (ii) a correlation analysis between body posture assessment scores and handwriting quality measures; and (iii) an evaluation of the immediate effects of interventions improving body posture on handwriting quality.

Related work

Importance of handwriting

Handwriting is a critical skill for children to acquire during their early education because it forms the basis of key activities such as paper-based exams, note-taking, and self-expression [17]. Christensen [18] revealed the strong link between good handwriting skills and academic success. And as schoolwork becomes increasingly cognitively demanding over time, children who struggle with handwriting may simultaneously struggle to manage other tasks such as grammar, orthography, and composition, which might lead to general learning difficulties and even failure [17,18]. Moreover, children with handwriting difficulties usually try to avoid writing tasks, which may eventually result in increased anxiety and lower self-esteem [12]. This in turn leads them to avoid training opportunities and sometimes results in school refusal [19]. Given the deep and long-lasting consequences that handwriting difficulties can have on children and their lives, we deem it of paramount importance to use and develop technological solutions that can support handwriting practice and the remediation of difficulties.

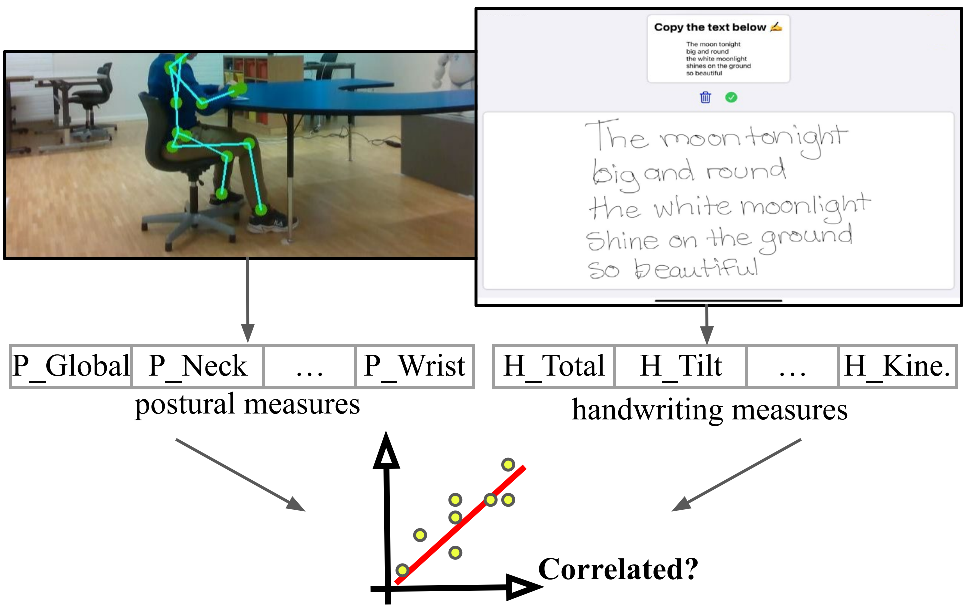

Fig. 1. This article investigates the relationship between body posture and handwriting quality, to pave a path for customising Child-Computer Interaction systems for handwriting training with the ability to provide real-time appropriate interventions. Body posture quality is assessed by computing validated ergonomics scores[15,16] on features extracted from RGB-D data, while handwriting quality is computed by the iPad app *Dynamilis* with the methodology proposed by Asselborn et al. [4].

Handwriting quality assessment

Several standard tests exist to assess handwriting quality and diagnose handwriting difficulties for different languages [20,21], all relying on the child writing using pen and paper, with an expert evaluating the child's handwritten piece, typically at a later point in time, on the basis of given references. For instance, the Rapid Assessment Scale for Children's Handwriting (BHK) is the *de-facto* standard for handwriting quality assessment in French speaking countries, which was created to detect dysgraphia in children at an early age[22].

Such methods suffer from a number of limitations: having the handwriting product graded by a human expert makes the whole process time-consuming, expensive and prone to subjectivity biases. Moreover, these methods only focus on the final handwriting product, with the dynamics of the writing process being entirely lost. With the emergence of digital tablets, novel handwriting assessment methods were conceived, taking the dynamics of handwriting into account [23–25]. Asselborn et al. [4] proposed a data-driven method to quantitatively evaluate handwriting on the basis of a number of low-level features, organized in the four categories of *tilt*, *static*, *pressure* and *kinematic*. A refined version of that method is currently employed by the iPad app *Dynamilis* [26], which provides the assessment in a few minutes. Considering the speed, objectivity and accuracy of the *Dynamilis* handwriting quality assessment, together with the possibility to examine handwriting along different dimensions, we decided to use it in this work as our handwriting quality assessment method.

Body posture quality assessment

Many methods have been developed over the past decades to evaluate a person's body posture quality from the biomechanical and ergonomic perspective, mainly with the aim of ensuring the comfort and efficiency of people in their working or daily life activities[15,16,27,28]. The New York Posture Rating (NYPR) scale evaluates people's physical fitness in clinical settings by assessing the proper or improper alignment of body segments. In the work of McRoberts et al. [29], for example, the NYPR scale was used to investigate the influence of posture support garments on body posture. However, the NYPR requires the subject to stand upright, which makes it an unsuitable reference for activities, such as handwriting, which usually take place while sitting.

A number of ergonomic scales have been developed, to analyse the postural attitude of workers at their workstations. The Ovako Working Posture Analysis (OWAS) [27] is meant to assess the postural risk of workplace tasks and environments, by evaluating the worker's body posture at regular intervals. The Rapid Entire Body Assessment (REBA) [15] and the Rapid Upper Limb Assessment (RULA) [16] are among the most widely used tools to assess the occupational postural risk, referenced by the International Ergonomics Association (IEA) and the World Health Organization (WHO) as an international standard [30].

The aforementioned methods are meant for on-site observation, which requires the work cell to be deployed before the postural assessment can be done. To overcome this limitation, the Task Analysis Toolkit (TAT) is a plugin assessment tool for the human factors simulation software *Jack* [31] allowing for performing ergonomic compliance checks directly within a 3D virtual environment. The Posture Evaluation Index (PEI) [28] relies on TAT and the virtual environment provided by *Jack* and integrates Lower Back Analyses (LBA), OWAS, and RULA to measure how ergonomic a body posture is. It was developed in 2006 and used to optimize the design of manufacturing work cells.

Since ergonomics typically focuses on workplace environments, only a handful of studies assess the quality of handwriting postures.[32] used PEI to assess the body posture quality during handwriting, in order to investigate the effect of having left-handed students work using a right-sided writing armchair. Among the three scales composing PEI, RULA was found to have the largest weight. Given the worldwide acceptance of REBA and RULA, together with the latter's use in the context of handwriting-related assessments, they are the scales we consider as references for body posture quality assessment in our study.

Body posture and handwriting correlation

While it has been widely assumed that a relationship exists between handwriting and body posture, to the best of our knowledge no in-depth, comprehensive studies have been done on the subject. The only study quantitatively exploring this relationship is found for the Hebrew language, where Parush et al. [11] used the *Hebrew Handwriting Evaluation* (HHE) method to jointly rate the body positioning score (measured by a human observer on a scale from 1 to 4) and a number of handwriting features including legibility, speed, etc. Their findings revealed that some handwriting features, such as the number of unrecognizable letters and subjective legibility, are significantly correlated with the body positioning score. However, their methodology relies on human observers, and thus cannot be directly ported onto fully automated CCI systems, nor can be considered devoid of the typical human biases and limitations. More recently, Dziedzic [33] explored the effects of lying down posture on handwriting, specifically investigating whether handwriting features vary between two different lying postures. However, the correlation between postural elements and handwriting quality was not addressed in the study. In the study of Wang et al. [34], a correlation was observed between handwriting quality and changes in posture among children. However, it is worth noting that only head posture was monitored during the experiment. As outlined in the Introduction, we postulate that developing methods allowing for the objective analysis of the correlation between body posture quality and handwriting quality is not only important to expand our knowledge of the handwriting process, but also key for designing effective training activities and interventions, that can be conducted or mediated by autonomous CCI systems.

Methods

Automated body posture quality assessment

As described in the "Related work" Section, REBA and RULA are widely used, validated standard scales for posture quality assessment. REBA is a systematic measure to evaluate ergonomic risk factors associated with postures and tasks [15]. Concretely, the REBA scale follows a bottom-up approach to build an overall score (which ranges from 1 to 13 with steps of 1) as the aggregation of independent sub-scores associated with different body parts (listed in Table 2), plus a number of sub-scores related to the activity to be performed in that posture and the forces/loads at play. Higher values represent worse posture quality. Conversely, RULA was developed to specifically evaluate the ergonomic state associated with the upper limb and neck extremities, using a scale going from 1 ("good posture"), to 7 ("bad posture") [16]. Like for REBA, the overall RULA score is built as the aggregation of sub-scores, specifically focusing on neck, trunk, legs, upper arms, lower arms, wrists, wrist twist, muscle use and forces/loads. In both scales, the sub-score is determined on the basis of reference tables [35,36], which associate a score to different joint configurations. In the context of handwriting, a proper body posture [9] is generally characterized by the following: the neck is flexed slightly forward, allowing the child to look down at the paper or tablet without excessive tilting or twisting; the trunk remains upright, with minimal forward lean or side bending; the upper arms are relaxed and close to the torso, with elbows bent at approximately 90 degrees; the lower arms rest comfortably on the desk surface without excessive elevation or rotation; and the wrists are kept in a neutral position, avoiding extreme flexion, extension, or deviation. Note that sub-scores referring to the activity, coupling and forces/loads at play are not discussed in this work, since they are constant for the handwriting activity.

REBA and RULA require computing the relative position of different body parts: we argue that state-of-the-art RGB-D cameras and skeleton tracking software allow for the automated, rea-time and easily deployable computation of REBA and RULA, with a rate and accuracy surpassing those of human observers. The pipeline we propose to this end, shown in Fig. 2, relies on the data stream provided by an RGB-D camera and the following steps executed on each frame: (i) 3D human body skeleton extraction, with the skeleton represented as a set of joints, each with a position, orientation, and confidence value; (ii) noise filtering on the joints confidence values (cutoff = 0.5) and smoothing of the joint movement with an exponential moving average filter (smoothing factor α = 0.7); (iii) extraction of the features (joint configurations) required for the computation of the REBA and RULA sub-scores; (iv) REBA and RULA scores computation via lookup tables for the feature values.

Run-time analysis

We computed the run-time performance of our pipeline on a laptop with Intel i7-11850H CPU 2.50GHz and NVIDIA RTX A4000 GPU in a test of 1000 iterations. The 3D skeleton extraction with *Nuitrack AI* and *Intel RealSense* depth camera D435 takes about 33.33 ± 3.85 ms per frame without GPU support, which is the same configuration we use in our experiment. Filtering and feature extraction take around 1.68 ± 0.27 ms, while the REBA and RULA score calculation only takes 0.08 ± 0.01 ms per skeleton. The complete end-to-end pipeline needs around 35.19 ms per frame, which is compatible with a system operating at the frequency of at most 28.41 fps. Thus the proposed pipeline can endow a CCI system with the ability to assess a child's posture in real-time.

Experiment

To objectively investigate the relationship between body posture quality and handwriting quality in an ecologically valid, fast and fully-automated way, we designed an experiment relying on the body posture quality assessment pipeline described in the previous Section and the handwriting quality assessment provided by the iPad app *Dynamilis*.

Automated handwriting quality assessment

The *Dynamilis* app functionality for handwriting quality assessment (shown in Fig. 1—right) requires the child to copy a standard text, writing on an iPad with an Apple Pencil. Low-level features related to the tilt of the pencil, the pressure applied via the pencil on the tablet, the movements done while writing (e.g., the speed and acceleration profiles) and the spatial characteristics of the final product (e.g., the distance between words) are analysed following the procedure outlined in the work of Asselborn et al. [4] to extract the tilt, pressure, kinematic and static sub-scores respectively, which are merged in the total handwriting quality score (henceforth referred to as HW score). All scores are normalized in the range [0,1], where a higher value indicates a better handwriting quality. The analysis is performed online and takes about 1 minute for completion.

Experiment design

The goal of the experiment is to answer the following questions:

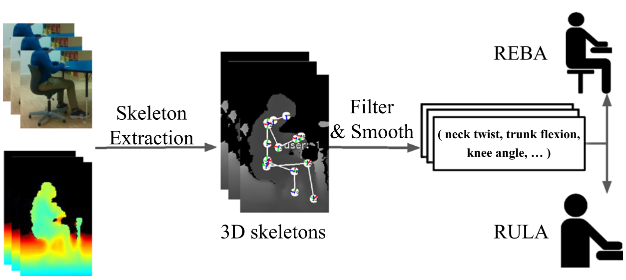

Fig. 2. Automated body posture quality assessment pipeline.

Fig. 3. The flow chart of the experiment procedure. The introduction phase is not included in the chart.

Variable	Characteristics	Frequency	Percent (%)
Age (years)	8	16	51.6
	9	14	45.2
	10	1	3.3
Sex	Girl	11	35.5
	Boy	20	64.5

Table 1. Participant demographics.

Q1: Is body posture quality (REBA and RULA scores) correlated with handwriting quality (HW score)? Is there a correlation between the body posture quality of specific body parts (REBA and RULA sub-scores) and specific handwriting dimensions (HW sub-scores)?
Q2: Do interventions aiming to improve the body posture quality have an immediate effect on handwriting quality?

To investigate these questions, we operationalized the body posture quality with REBA and RULA scores and sub-scores and handwriting quality with HW score and sub-scores. We designed an experiment in which: children are initially asked to engage in handwriting training activities for a certain amount of time, to ensure they fall onto their natural handwriting body posture; once they presumably are in their natural handwriting body posture, e.g., a slouch posture due to fatigue, a body posture correction intervention is performed to investigate the effect of posture change on handwriting quality. The detailed experiment procedure can be seen in Fig. 3.

Experimental setup
We employed an established Child-Robot Interaction system specifically designed to facilitate handwriting training support [37,38]. A social robot was included in the experimental setup, with the purpose of automating the entire interaction. As shown in Fig. 1 - left, the setup includes: (i) an iPad running the *Dynamilis* app, paired with an Apple Pencil, (ii) the social robot QTrobot [39] positioned in front of the child, approximately 1.5 m away, (iii) an external RGB-D camera to track the body posture of the child and (iv) a laptop coordinating the integration of the devices via ROS. The external camera is an *Intel RealSense* depth camera D435, placed on a tripod on the right side of the child (around 2 m away and 20° behind). The camera is operated with *RealSense Viewer* and captures the RGB-D video at 30 fps, where the resolution of the RGB camera is 640x480 and that of the stereo module is 848x480.

Experiment procedure
The session unfolds as shown in Fig. 3. At first, a researcher welcomes the child, outlines the structure of the experiment and briefly introduces the robot and the activities in the *Dynamilis* app. The child is also asked to try out the seat and adjust its position and height according to the child's preference. Then, the robot invites the child to sit down and perform the handwriting assessment test (referred to as *pre-test*) on the *Dynamilis* app. Afterwards, for approximately 15 minutes (referred to as *handwriting training phase*) the robot proposes different handwriting training activities on the tablet to the child, reacting with congratulatory or encouraging statements to the child's performance in the activities. The purpose of this phase is to let the child familiarize with *Dynamilis*, the handwriting quality assessment functionality and the robot, and fall onto their natural body posture while handwriting. At the end of this phase, the robot asks the child to perform another handwriting assessment (henceforth referred to as *mid-test*). At the end of the test, a researcher demonstrates the standard sitting posture [9] for handwriting to the child, inviting them to repeat the test one last time trying to maintain the showcased posture. This last handwriting quality assessment is the *post-test*. The whole session lasts approximately 30 minutes, with children taking 2-3 minutes to perform one handwriting test.

The analysis of the correlation between body posture quality and handwriting quality during the pre-test, mid-test and post-test allows for answering Q1, while the analysis of the change in body posture quality and handwriting quality from the mid-test to the post-test allows for answering Q2.

Participants
We invited 31 children (11 girls and 20 boys aged M = 8.52 years old, SD = 0.57, as Table 1) enrolled in two classes of grade three at a local international school to take part in the study. Teachers took care of sharing the information sheets and consent forms with the children and their parents. The children come from diverse cultural and socioeconomic backgrounds and all use spoken and written English in their daily life at school. One had previously used the *Dynamilis* app. Two participants abandoned the experiment prior to its completion and

two are left-handed (which made the posture quality assessment unreliable due to the camera's positioning) thus leaving us with the data of 27 participants for the analysis.

Ethical statement This study has received ethical approval from the Human Research Ethics Committee (HREC) of the Swiss Federal Institute of Technology in Lausanne (EPFL) under protocol HREC 057-2021 and was conducted in accordance with the Declaration of Helsinki. All parents of children gave their informed consent in writing.

Data processing

We collected the handwriting quality assessment scores, of all tests, of all participants, from the *Dynamilis* app Firestore database. No post-processing is needed.

The raw RGB-D camera data were stored as ROS bag files and processed offline following the body posture quality assessment pipeline. Concretely, we used the out-of-the-box *Nuitrack SDK*[40] ,which is an industrial-leading 3D body tracking middleware compatible with *RealSense D435* camera, with the CNN_HPE skeletonization type and *Depth to Color Registration* enabled. All the other configurations were in default settings. This setup enables the Nuitrack to output the 3D human body skeleton represented as a set of 24 body joints. Fig. 4 gives an example of the evolution of the REBA and RULA scores during a part of one handwriting test, for one of our participants. For both scales, the overall body posture quality score associated with a test is defined as the average score over time during the test execution. And the postural score will not be computed in the software by design if the average confidence value of the right body joints is less than 0.5. Please notice that while REBA and RULA scores can be computed for either side of the human body, in this experiment we exclusively focused on the right side of the participant (i.e., using the right body joints plus those in the sagittal plane), due to the positioning of the camera.

Statistical analysis

To assess the relationship between body posture quality and handwriting quality, we conducted non-parametric Spearman's rank correlation analyses between REBA/RULA scores and the handwriting quality scores (total and sub-scores) for both the mid-test and post-test. This allowed us to identify monotonic relationships between posture variables and handwriting performance. To evaluate the effect of the handwriting training phase and body posture intervention, we applied: Paired Student's T-tests to compare REBA and RULA scores across pre-test, mid-test, and post-test phases and Wilcoxon signed-rank tests for comparisons of handwriting quality scores across conditions, as some of the score distributions deviated from normality [4]. We also performed post-hoc power analyses using G*Power 3.1 to evaluate the statistical power of our tests, considering an alpha level of .05 for significance thresholds.

Results

On the correlation between body posture quality and handwriting quality scores: REBA

To investigate the relationship between body posture quality and handwriting quality [Q1] we performed a two-sided Spearman's rank correlation analysis on the body posture quality score and handwriting quality score, on the result of the mid-test and post-test separately. Please notice that in this section we exclusively focus on REBA as body posture quality score. The additional insights brought by RULA are reported in the next section. The Spearman correlation coefficient r and p values are summarized in Fig. 5. The higher the coefficient r is, the more similar ranks two observations have. Our hypothesis is that children with a better body posture (i.e., a lower REBA score), also have a better handwriting (i.e. a higher HW score), hence we expect the two scores to be negatively correlated. A post-hoc power analysis using G*Power 3.1[41] was also conducted to evaluate the power of the two-sided Spearman's correlation analysis based on α level of .05.

In the correlation heatmap of Fig. 5 negative correlation is represented by the color blue, while positive correlation is marked in red, and stars denote statistical significance. For the mid-test, as Fig. 5a shows, we found

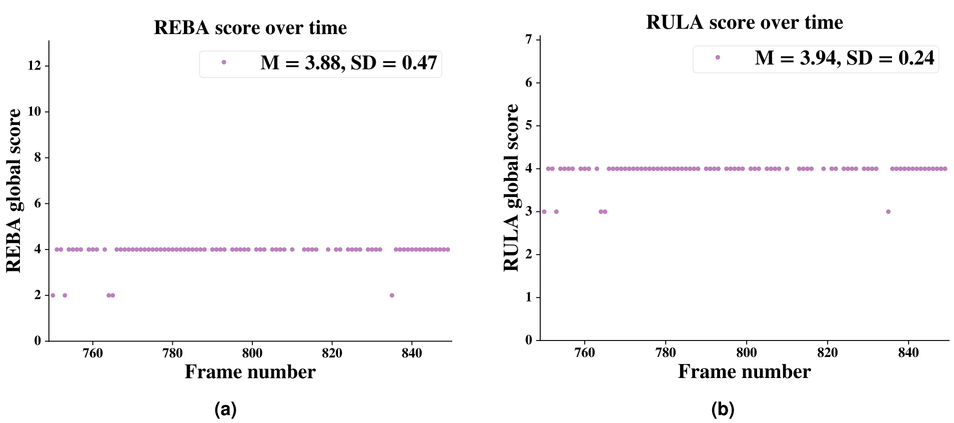

Fig. 4. Evolution of the REBA (**a**) and RULA (**b**) scores during a part of one handwriting test. The overall score is computed as the average of the frame-specific scores, over the interval of interest.

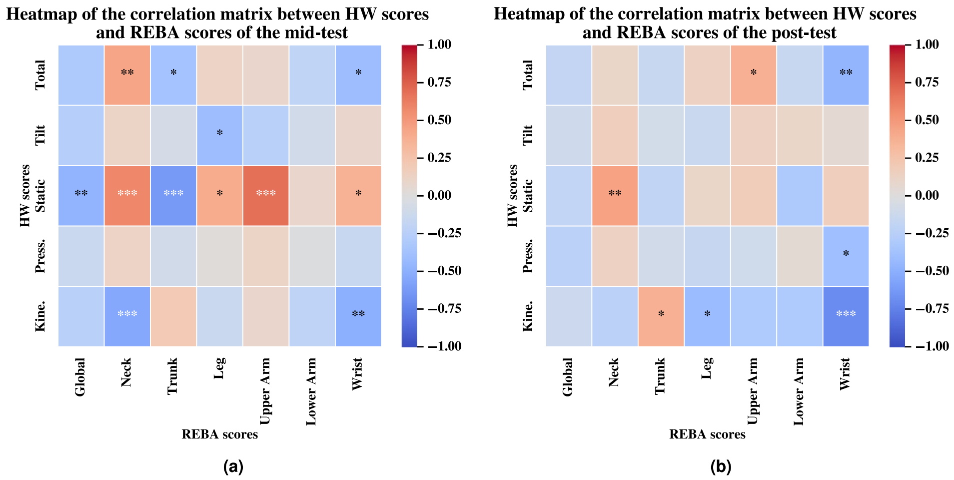

Fig. 5. The heatmap of the Spearman correlation matrix between the HW scores and REBA scores, at the mid-test (**a**) and post-test (**b**). The value of the correlation coefficient *r* is encoded by the color while the corresponding *p* value is reported with the asterisks convention: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

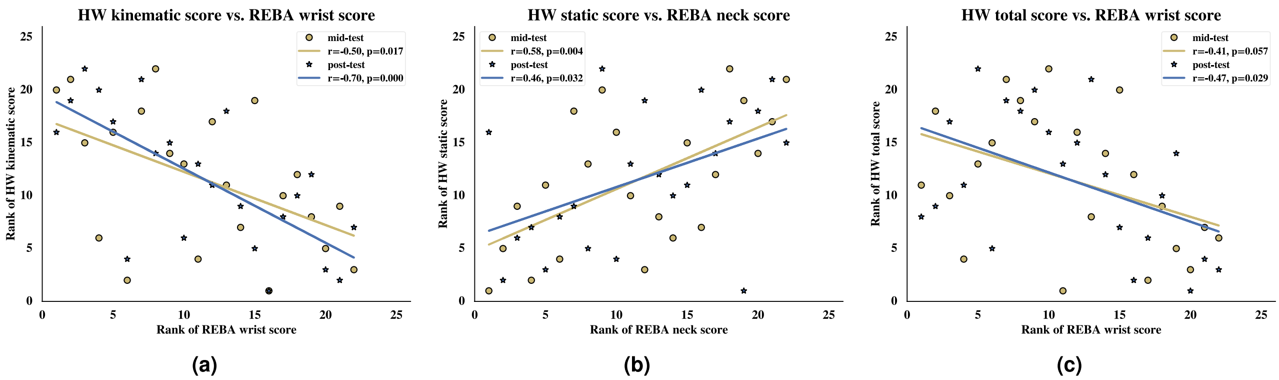

Fig. 6. Scatter plots of the Spearman's rank correlation between HW scores and REBA scores for both the mid-test and post-test: The *x* axis of each plot represents the rank of certain REBA score and the *y* axis is for the rank of certain HW score. There are two groups (mid-test and post-test) of data points indicated by different colors in each plot and a linear regression line is drawn for each group.

a significant negative correlation between multiple sub-scores. The significant negative correlation was observed between:

- HW static score and REBA global score ($r = -0.47$, $p < 0.05$) with an observed power of 0.72,
- HW static score and REBA trunk score ($r = -0.62$, $p < 0.01$) with an observed power of 0.95,
- HW kinematic score and REBA neck score ($r = -0.54$, $p < 0.01$) with an observed power of 0.86,
- HW kinematic score and REBA wrist score ($r = -0.50$, $p < 0.05$) with an observed power of 0.78.

While the above results are in line with our hypothesis, others disprove it. Specifically, there was a significant positive correlation between:

- HW static score and REBA neck score ($r = 0.58$, $p < 0.01$) with an observed power of 0.91,
- HW static score and REBA upper arm score ($r = 0.68$, $p < 0.01$) with an observed power of 0.98.
- HW total score and REBA neck score ($r = 0.44$, $p < 0.05$) with an observed power of 0.65.

To verify the consistency of our findings, as shown in Figs. 5b and 6, the same correlation analysis was also performed on the post-test. In line with the mid-test findings, we found a strong negative correlation between the HW kinematic score and REBA wrist score ($r = -0.70$, $p < 1e\text{-}3$), as well as fair negative correlation between the HW total score and REBA wrist score ($r = -0.47$, $p = 0.029$), with an observed power of 0.99 and 0.72 respectively. Moreover, as in the mid-test, The HW static score exhibited a fair positive correlation with the REBA neck score ($r = 0.46$, $p = 0.032$). The post-hoc G*Power analysis observed a power of 0.70. To further corroborate the validity of our findings, no statistically significant correlation found in the post-test is in contrast with a statistically significant correlation found in the mid-test.

Item	Global	Neck	Trunk	Leg	Upper arm	Lower arm	Wrist
Pre-test	5.21 ± 0.80	2.77 ± 0.17	1.86 ± 0.55	2.91 ± 0.19	1.48 ± 0.35	1.04 ± 0.07	1.07 ± 0.05
Mid-test	5.36 ± 0.73	2.73 ± 0.17	2.14 ± 0.54	2.92 ± 0.16	1.48 ± 0.28	1.07 ± 0.07	1.08 ± 0.05
Post-test	5.01 ± 0.52	2.82 ± 0.11	1.71 ± 0.36	2.97 ± 0.10	1.57 ± 0.30	1.15 ± 0.20	1.06 ± 0.04
	Pre-test vs. Mid-test						
T stat.	0.87	1.28	2.07	1.29	0.08	2.21	1.36
p value	0.391	0.211	0.048**	0.208	0.937	0.036**	0.184
Cohen-d	− 0.20	0.23	− 0.49	− 0.06	− 0.02	− 0.41	− 0.26
	Mid-test vs. Post-test						
T stat.	2.31	2.39	3.81	1.27	1.01	1.90	2.69
p value	0.029**	0.024**	<1e−3***	0.215	0.323	0.068*	0.012**
Cohen-d	0.54	− 0.61	0.88	− 0.37	− 0.28	− 0.48	0.48

Table 2. REBA scores (mean ± sd) at pre-test, mid-test and post-test, with T statistics and effect size (*p <0.1, **p <0.05, ***p <0.01).

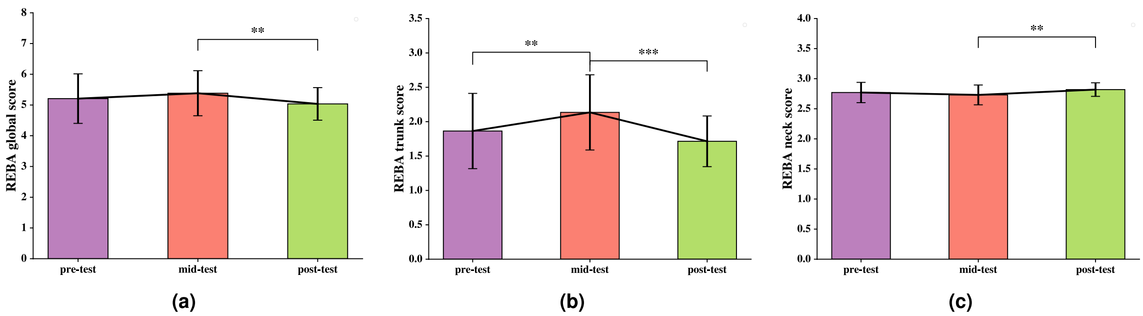

Fig. 7. The REBA global (**a**), trunk (**b**) and neck (**c**) scores at pre-test, mid-test and post-test. The corresponding p value is reported with the asterisks convention: *p <0.1, **p <0.05, ***p <0.01.

On the correlation between body posture quality and handwriting quality scores: RULA

RULA and REBA share the exact same methodology to construct the trunk, upper arm and lower arm scores. Since the results of our analysis for these sub-scores are identical, we discard them in the following analysis.

In line with the REBA findings, the RULA wrist score was found to be negatively correlated with the HW kinematic score, both in the mid-test (r = − 0.50, p = 0.018) and in the post-test (r = − 0.66, p < 1e-3). Additionally, the same significant positive correlation was found between RULA neck score and HW static score, both in the mid-test (r=0.57, p = 0.006) and in the post-test (r = 0.51, p = − 0.015). Additionally, no statistically significant correlation found for RULA was in contrast with a statistically significant correlation found for REBA.

On the effects of the handwriting training phase: pre-test vs. mid-test

On body posture quality scores

One assumption of the experiment design is that the body posture of children at the beginning of the experiment could not persist for a long period and their posture naturally deteriorated over time. The result of a two-sided paired Student's T test on the REBA/RULA scores between pre-test and mid-test conformed to this assumption. In addition, the Cohen's effect size d was computed. As shown in Table 2 and Fig. 7, comparing the REBA scores between before and after the handwriting training phase, the global score increased from 5.21 to 5.36 (Fig. 7a), but the difference was not statistically significant ($t(26) = 0.87$, $p = 0.391$, $Cohen\text{-}d = -0.20$). With the sole exception of the neck score (Fig. 7c), which decreased by 1%, all REBA sub-scores increased from the pre-test to the mid-test, thus denoting a deterioration in body posture quality. Specifically, a statistically significant difference was found on the REBA trunk score (Fig. 7b), $t(26) = 2.07$, $p = 0.048$, $Cohen\text{-}d = -0.49$, whose mean value increased by 15%, indicating that children significantly bent their body trunks due to the long handwriting training phase. Based on α level of .05, the post-hoc G*Power analysis observed a power of 0.69 on the two-sided Student's T test. Similarly, the REBA lower arm score increased by 3% ($t(26) = 2.21$, $p = 0.036$, $Cohen\text{-}d = -0.41$) with an observed power of 0.54.

Once again, the results of the RULA scores were in line with those of REBA. The global score increased from 4.07 to 4.12 without statistically significance, ($t(26) = 0.82$, $p = 0.420$, $Cohen\text{-}d = -0.19$). All the mean sub-scores of RULA except for the neck score increased as well. And the same statistically significant increases were found on RULA trunk and lower arm scores due to the same definition.

Item	Total	Tilt	Static	Pressure	Kinematic
W stat.	133.0	162.0	150.0	158.0	119.0
p val.	0.442	0.999	0.751	0.916	0.252
Cohen-d	-0.22	-0.11	-0.13	-0.08	0.16

Table 3. Two-sided Wilcoxon T statistics and effect size on HW scores between pre-test and mid-test.

Item	Total	Tilt	Static	Pressure	Kinematic
Pre-test	0.39 ± 0.16	0.34 ± 0.18	0.47 ± 0.11	0.39 ± 0.20	0.38 ± 0.19
Mid-test	0.43 ± 0.21	0.36 ± 0.20	0.48 ± 0.12	0.41 ± 0.21	0.35 ± 0.16
Post-test	0.41 ± 0.17	0.40 ± 0.19	0.49 ± 0.12	0.44 ± 0.20	0.39 ± 0.19

Table 4. HW scores (mean ± sd) at pre-test, mid-test and post-test.

On handwriting quality scores
To investigate the potential improvement of the handwriting quality scores induced by the handwriting training phase, a two-sided Wilcoxon T test was conducted, since not all handwriting dimensions were found to follow the normal distribution [4]. As shown in Table 3 and Table 4, there was no statistically significant difference in any of the dimensions of handwriting quality between pre-test and mid-test, which is in line with the fact that handwriting skill acquisition is a long-term process [42] thus not significantly affected by a 15-minutes handwriting training.

On the effects of the body posture intervention: mid-test vs. post-test

On body posture quality scores
A necessary precondition for the investigation of the effects that improving one's body posture quality has on handwriting quality [Q2] is to verify that the body posture intervention we conducted had a significant positive effect on the children's body posture quality. To this end, a two-sided paired Student's T test was conducted to detect whether there was a statistically significant difference between the mid-test REBA/RULA scores and the post-test REBA/RULA scores. A post-hoc power analysis using G*Power was also conducted to evaluate the power of the Student's T test based on α level of .05.

As shown in Table 2 and Fig. 7, a statistically significant difference was found on the REBA global score, $t(26) = 2.31$, $p = 0.029$, whose mean value decreased from 5.36 to 5.01 with medium effect size (*Cohen-d* $= 0.54$). The observed power was 0.77. This result indicates that the body posture intervention globally significantly improved the body posture of the children. As the table shows, the most significant improvements concern the trunk score, which decreased by 20.09%, with large effect size and an adequate observed power of 0.99, ($t(26) = 3.81$, $p < 1e-3$, *Cohen-d* $= 0.88$), and the wrist score, which dropped from 1.08 to 1.06, ($t(26) = 2.69$, $p = 0.012$). Conversely, there was a significant increase in the neck score after the posture intervention ($t(26) = 2.39$, $p = 0.024$), with medium effect size (*Cohen-d* $=$ -0.61) and an adequate observed power of 0.86. This result indicates that the angle of neck flexion, which is the movement bringing the chin towards the trunk, was increased after the body posture intervention. An intuitive explanation for this finding is that since children kept their trunk straighter during the post-test, they might have flexed the neck more as a compensatory motion to keep their focus on the tablet.

Regarding RULA, the global score dropped from 4.12 to 4.05, but the difference was not statistically significant, ($t(26) = 1.23$, $p = 0.229$, *Cohen-d* $= 0.30$). Since RULA, w.r.t. REBA, poses a greater focus on the upper limbs, this result is in line with the above finding that the most notable improvement concerned the trunk. The statistically significant findings at the level of the RULA sub-scores are in line with those of REBA. The wrist score significantly decreased from 1.36 to 1.29 ($t(26) = 2.87$, $p = 0.008$, *Cohen-d* $= 0.52$), while the neck score increased from 3.61 to 3.75 ($t(26) = 2.39$, $p = 0.024 < 0.05$, *Cohen-d* $= -0.62$), with an observed power of 0.73 and 0.87 respectively.

We can thus conclude that our intervention had a globally positive, noticeable effect on the children's posture quality.

On handwriting quality scores
To compare the handwriting quality scores between the mid-test and post-test, a two-sided Wilcoxon T test was conducted. The results of the comparison are reported in Table 4 and Fig. 8. There was no statistically significant difference in total score, tilt score, static score and pressure score. However, at the same time, the Wilcoxon test indicated that the average kinematic score increased by 11.4% after the body posture correction ($W = 82.0$, $p = 0.030$). Based on α level of .05, the post-hoc power analysis with G*Power had an observed power of 0.74. This finding suggests that a good body posture might have a direct positive impact on the kinematic aspects of handwriting, such as the speed and the in-air-time of the pen.

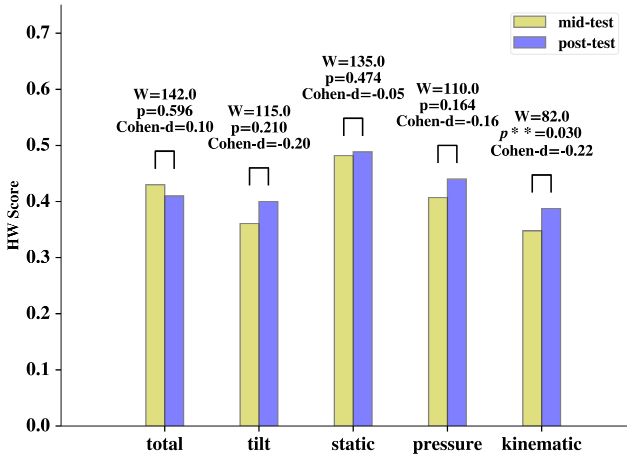

Fig. 8. Comparison between the HW scores at the mid-test and post-test with Wilcoxon T test.

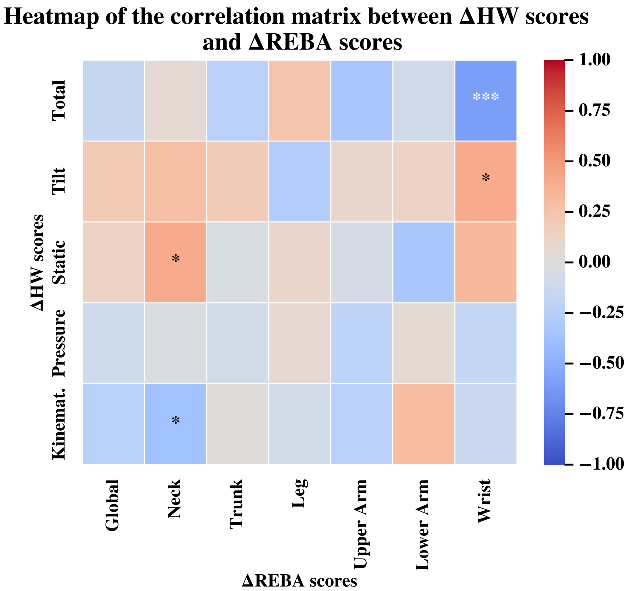

Fig. 9. The heatmap of the Spearman correlation matrix between the mid-post change of HW scores and the mid-post change of REBA scores. The value of the correlation coefficient r is encoded by the color while the corresponding p value is reported with the asterisks convention: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

On the correlation between variations in body posture quality scores and handwriting quality scores

As a follow-up on the previous analysis, we also checked whether variations in body posture quality scores, from the mid-test to the post-test, are correlated with variations in handwriting quality scores. The results of the two-sided Spearman's rank correlation between REBA and HW scores are reported in Fig. 9, where Δ_X denotes the difference in X between its mid-test and post-test values. The only statistically significant correlation was between ΔHW total score and ΔREBA wrist score, ($r = -.60$, $p<.01$), indicating that children who greatly improved their HW total score also greatly improved their wrist posture quality. Based on α level of .05, the post-hoc power analysis with G*Power had an observed power of 0.93, which indicates that the test was adequately powered. Moreover, a marginally significant fair negative correlation was found between ΔHW kinematic score and ΔREBA neck score ($r = -0.38$, $0.05 < p < .1$). Lastly, marginally significant fair positive correlations were found between ΔHW tilt score and ΔREBA wrist score, and between ΔHW static score and ΔREBA neck score ($r > 0.40$, $0.05 < p < 0.1$).

As to the correlation analysis between the variation of RULA scores and HW scores, the same correlation between Δwrist score and ΔHW total score was found, with marginal significance ($r = -0.41$, $p = 0.056$).

Discussion
Our findings not only (i) reveal the existence of correlations between specific postural elements quality assessment scores (e.g., the neck score) and handwriting dimensions (e.g., static components such as the spacing between words), but also (ii) suggest that interventions aiming to improve body posture quality also have an immediate, significant positive effect on handwriting quality. These findings, albeit preliminary, provide compelling evidence for building a handwriting training system where the system's ability to continuously assess a child's posture in a fast, reliable and objective way, combined with the found correlation between body posture improvements and handwriting quality improvements, allows for new forms of training activities and interventions.

Correlations
The outcomes of the user study provided us with statistical evidence regarding the correlation between the quality of specific body posture element and handwriting dimension as presented. As shown in Fig. 6a , we found a statistically significant negative correlation between the HW kinematic score and REBA wrist score ($r = -0.50$ in mid-test and $r = -0.70$ in post-test), which means that the pose of the wrist is moderately to strongly related to pen dynamics during writing (e.g., the handwriting speed [4]). Specifically, the REBA/RULA wrist score mainly measures the wrist flexion [15,16], with a neutral wrist pose having the lowest score. Ample research in the field of bio-mechanics pointed out that wrist poses have effects on hand gripping endurance [43], gripping strength [43], and hand dexterity [44]. Intuitively, our findings suggest that a flexed wrist might decrease the dexterity of the hand gripping the pen, which is related to poor handwriting kinematic score. The post-hoc power analysis for the Spearman's correlation test in the post-test also indicated a power of 0.99, suggesting the study is adequately powered to detect such a result, although the observed power of 0.78 in the mid-test is slightly below the conventional threshold of 0.80.

In addition, as shown in Fig. 6b , it was noticed that the angle of neck flexion of the children is correlated with the HW static score (moderate in the mid-test and fair in the post-test), which generally captures how the final handwriting product looks like. Thus we can infer that, in our study, children who tended to flex their necks also produced handwriting samples with better spatial characteristics. The observed statistical power of 0.91, based on the post-hoc G*Power analysis for the Spearman's correlation test during the mid-test, indicates that the study was adequately powered to detect the observed effect, minimizing the risk of a Type II error. The post-test demonstrated a statistical power of 0.70, suggesting that the test had moderate power. Future research with a larger sample size may help achieve a higher power.

The variation of handwriting body posture of children
In this experiment, we evaluated children's posture at three different stages. Initially, at the pre-test, the children exhibited postures shaped by personal habits and varying mental or physical states. After about 15 minutes of handwriting training, children likely settled into their more natural and familiar postures, as evidenced by the increase in trunk scores (Fig. 7b) from the pre-test to mid-test. The posture correction intervention significantly impacted their body posture, as shown by the Student's T test (Table 2, see part *Mid-test vs. Post-test*). These findings emphasize the importance of posture dynamics in educational contexts, highlighting how posture shifts within just 15 minutes of activity and how posture improvement can directly influence handwriting quality. Therefore, body posture not only serves as an indicator but can also be a lever for interventions that support learning. In addition, a two-sided Student's T test was performed by comparing the postural scores between pre-test and post-test and the only statistically significant difference was found on the lower arm score ($t(26) = 2.77$, $p = 0.010$, $Cohen\text{-}d = -0.68$). Thereby a conclusion cannot be drawn with regard to whether the children's initial body postures is already close to the correct body posture.

Ergonomic body posture quality scale vs. handwriting body posture quality scale
To the best of our knowledge, there is no quantitative measure specifically evaluating the quality of one's body posture for handwriting activities so far. In our study, we relied on the REBA/RULA scales, which are validated ergonomic scales, as the proxy to evaluate the body posture quality during handwriting. However, our findings reveal that a better handwriting is not necessarily associated with an ergonomically better body posture. For instance, the best ergonomic posture for the neck, according to the REBA/RULA scales, implies that the person looks straight ahead. However, this is impractical for the purposes of handwriting, which requires to tilt the neck towards the chest, to have a clear view on the desk. Indeed, our study revealed that the neck score significantly increased (i.e., worsened from an ergonomic point of view) after the posture correction intervention. Future works from our part will include the design and validation of methods for body posture quality assessment measures that are specifically tailored for handwriting activities. Furthermore, REBA and RULA scores represent aggregated ergonomic risk levels rather than precise postural measurements. For instance, the same neck score can result from different combinations of flexion, twisting, or side-bending. Therefore, our findings reflect correlations between handwriting quality and overall posture risk scores, which are related to discrete postural configurations. Future work might consider analyzing raw joint angles to link specific posture features with handwriting outcomes.

Limitations and future work
While our work sheds new light on the relationship between handwriting and body posture quality scores, a number of limitations should be highlighted. Firstly, the participants of this study were recruited from two classes in the same grade and same school: it would be worthwhile to extend the study to more subjects, with more diverse backgrounds, e.g., students from different schools. Secondly, we took a snapshot at a specific age and while this is valuable in itself, it is important to repeat the study with children of different ages to analyse the evolution of the correlation over time. Besides, all the children in this study wrote in English and most of them

are right-handed: investigating the transferability of our analysis results to other languages and to left-handed children would allow for characterizing the influence of other factors (handedness and script) on the correlation. Lastly, in our method, the body posture quality during a handwriting test was computed as the average score over the activity duration. While this can be a viable solution for short activities (as shown by Fig. 4, where the REBA and RULA global values appear to be constant throughout one handwriting test), longer activities will likely require different and more sophisticated methods of aggregation and analysis. For instance, an analysis of the temporal features of body postures, e.g., the angular speed of the elbow, and their correlation with handwriting features is an important goal for future work.

In this study, correlations on multiple pairs of postural elements and handwriting dimensions were identified. Although correlation does not indicate causality, our study still revealed some insights into the causal relationship between body posture quality improvement and handwriting quality improvement due to the fact that the HW scores were not significantly changed by the handwriting training phase (before the body posture intervention) and instead significantly improved in the kinematic dimension immediately after the body posture intervention. Future studies will be designed to investigate the pairwise causal relationship between body posture and handwriting quality by changing specific body posture element and comparing with a control group. Establishing the causality is important to determine whether we can use body posture as a lever to improve handwriting: knowing the direction of the causal link can instruct the design of CCI systems, specifically to properly integrate and make good use of body posture in their interventions.

Suggestions on the design of CCI system for handwriting training support

The experimental system already gives us a glimpse of such an effective CCI system for handwriting training support: the child practices handwriting on a digital tablet, with an external camera positioned to monitor his/her body posture. According to the correlation revealed in this study, body posture quality can act as an indicator to predict handwriting difficulty. For instance, based on the correlation between HW kinematic score and wrist score in Fig. 6a , we can predict the child may not have a good HW kinematic score when a high REBA wrist score is computed by the system. Then, in case the existence of a causal link between body posture quality and handwriting quality is confirmed, we can use body posture as a lever. For instance, if there is a causal relationship between trunk flexion and the kinematic dimension of handwriting quality, the system can alert the child to correct his/her trunk pose timely when the HW kinematic score computed by the application drops significantly. While such an educational CCI system is no match for human teachers and therapists in supporting a child practice handwriting, handwriting is a too fundamental skill, that too many children (one in three [2]) struggle with, to disregard the help that technology and automation can provide. We argue that an autonomous CCI system able to assess a child's body posture and handwriting quality, and equipped with a rich and diverse portfolio of validated interventions, can complement curricular practice and help reduce the number of children with handwriting difficulties.

Conclusion

In this paper, we propose a pipeline for the automated, real-time assessment of the body posture quality, which computes the REBA and RULA scores on 3D human skeletons extracted from RGB-D data. Combining this pipeline with the automated handwriting assessment performed by the iPad app *Dynamilis* allows for a quantitative analysis of the correlation between the quality assessment scores of one's body posture and their handwriting quality measures, in a way which, by removing the need for human observers, mitigates the errors introduced by humans' subjectivity. To the best of our knowledge, this is the first data-driven study of this correlation.

Using the data collected from 31 children aged 8–9 years old, we acquired evidence of a statistically significant correlation between the quality of specific body posture element and handwriting dimension, specifically suggesting that: (i) wrist quality scores are directly negatively correlated with the quality of the handwriting's kinematics (i.e., the speed of the movement); (ii) neck score is positively correlated with the quality of the handwriting's statics (i.e., features related to the appearance of the letters, such as the distance between words). At the level of variations, improvements in the wrist score (concretely, minimizing the angle between the wrist and the lower-arm direction) were found to be moderately negatively correlated with improvements in the overall handwriting quality. Lastly, our work provides empirical support that a simple intervention aiming to help the children improve their body posture has not only immediate positive effects on their body posture quality, but also on their handwriting quality: this finding, refined by future studies, constitutes a fundamental step towards the design of CCI systems for handwriting training support.

Data availability

The raw datasets generated and analyzed during the current study are not publicly available due to ethical requirements. The fully anonymized and aggregated data is available under request to the corresponding author, C.W.

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Author contributions
C.W. developed the system and conceived, and conducted the experiment, D.T. and B.B. conceived the experiment, and C.W. and D.T. analysed the results. C.W., D.T. and B.B. wrote the main manuscript text. All authors reviewed the manuscript.

Declarations

Competing interests
The authors declare no competing interests.

Additional information
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