Can Children Benefit from Technological Applications for Body Posture Correction to Improve Handwriting? A Study to Quantitatively Investigate the Correlation between Body Posture and Handwriting Quality

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Abstract

Various technological applications for body posture correction have been proposed in order to improve handwriting or facilitate its learning for children, under the common-sense 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 RGB-D data to compute the REBA/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 and handwriting quality, as well as (ii) the impact that interventions aimed at improving the children's body posture have on their handwriting quality.

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1 Introduction

Think of how common written exams are throughout the school system: handwriting is a fundamental skill to acquire because, from a very young age onward, it is a means to express one's ideas and knowledge in a wide variety of disciplines and contexts. At the same time, handwriting is a complex skill to acquire, which typically takes around 10 years to master (Accardo, Genna, & Borean, 2013). It is therefore not surprising, but tragic, that nearly one-third of all children between 4 and 12 years are affected by different levels of handwriting difficulties (Smits-Engelsman, Niemeijer, & van Galen, 2001).

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 (Plimmer, Crossan, Brewster, & Blagojevic, 2008), automated handwriting analysis and exercise games with digital tablets (Asselborn et al., 2018), engagement maintenance and confidence restoration with social robots (Hood, Lemaignan, & Dillenbourg, 2015), etc.

More specifically, various research works and commercial products focus on promoting a correct body posture for handwriting. 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 (Fan, Zheng, & Zhang, 2009). To tackle the same problem via a different approach, Luo (2015) 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 and Chen (2012) 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 standard body posture for handwriting (Graham & Weintraub, 1996) as a reference, defined 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 supported by common sense, is not yet sustained by conclusive scientific evidence in the field of education and information technologies (Blote & Heijden, 1988; Parush, Levanon-Erez, & Weintraub, 1998). We argue that characterizing the interplay between body posture and handwriting quality is crucial for the design of effective Child-Computer Interaction (CCI) systems aiming to provide handwriting training interventions, which can be tailored on a child's 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 (Blote & Heijden, 1988; Gargot et al., 2021; Parush et al., 1998). 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 (Kim, Sung, Saakes, Huang, & Xiong, 2021; Manghisi et al., 2017). 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 RGB-D camera for the automated real-time assessment of body posture quality, which computes the Rapid Entire Body Assessment (REBA) (Hignett & Mcatamney, 2000) and Rapid Upper Limb Assessment (RULA) (Mcatamney & Corlett, 1993) 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 (Asselborn et al., 2018), 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.

Our findings not only (i) reveal the existence of correlations between specific postural elements (e.g., the neck inclination) 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.

The contribution of this article is three-fold: (i) a publicly-available pipeline for the automated, real-time assessment of body posture quality using a single RGB-D camera; (ii) a data-driven analysis of the correlation between body posture quality and handwriting quality; (iii) an evaluation of the immediate effects that interventions aiming at improving body posture quality have on handwriting quality.

The article is organized as follows. Section 2 surveys relevant literature on handwriting and body posture quality assessment. Section 3 describes the proposed automated body posture quality assessment pipeline. Section 4 details the user study we conducted, while the results of the analyses are presented in Section 5. Section 6 discusses key findings, alongside limitations and future work. The suggestions for the design of an educational CCI system for handwriting training support are presented in Section 7. At last, we conclude our work in Section 8.

2 Related Work

2.1 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 (K.P. Feder & Majnemer, 2007). Christensen (2009) 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 (Christensen, 2009; K.P. Feder & Majnemer, 2007). Moreover, children

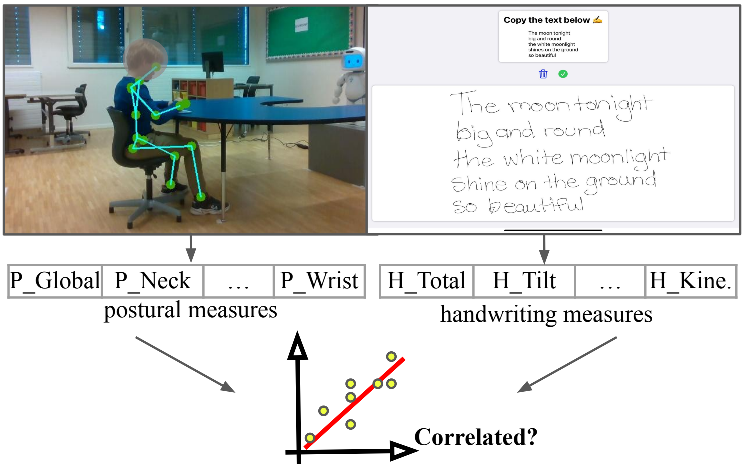


Fig. 1 This article investigates the relationship between body posture and handwriting quality, to pave a path for customising Child-Computer Interaction systems for handwriting training with the ability to provide real-time appropriate interventions. Body posture quality is assessed by computing validated ergonomics scores (Hignett & Mcatamney, 2000; Mcatamney & Corlett, 1993) on features extracted from RGB-D data, while handwriting quality is computed by the iPad app *Dynamilis* with the methodology described in (Asselborn et al., 2018).

with handwriting difficulties usually try to avoid writing tasks, which may eventually result in increased anxiety and lower self-esteem (Gargot et al., 2021). This in turn leads them to avoid training opportunities and sometimes results in school refusal (K. Feder, Majnemer, & Synnes, 2000). 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.

2.2 Handwriting Quality Assessment

Several standard tests exist to assess handwriting quality and diagnose handwriting difficulties for different languages (Barnett, Henderson, Scheib, & Schulz, 2009; Charles, Régis, & Albaret, 2003), 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 (Hamstra-Bletz, DeBie, Den Brinker, et al., 1987).

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 (Burget et al., 2023; Mekyska et al., 2016; Rosenblum & Dror, 2016). Asselborn et al. (2018) 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*[1], 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.

2.3 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 (Caputo, Gironimo, & Marzano, 2006; Hignett & Mcatamney, 2000; Karhu, Kansi, & Kuorinka, 1978; Mcatamney & Corlett, 1993). 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, Cloud, and Black (2013), 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) (Karhu et al., 1978) 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) (Hignett & Mcatamney, 2000) and the Rapid Upper Limb Assessment (RULA) (Mcatamney & Corlett, 1993) 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 (Occhipinti & Colombini, 2012).

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* [2] allowing for performing ergonomic compliance checks directly within a 3D virtual environment. The Posture Evaluation Index (PEI) (Caputo et al., 2006) 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. Rasyad and Muslim (2019) 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.

[1] https://dynamilis.com/en/
[2] https://www.simsol.co.uk/products/human-factors-simulation/jack/

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.

2.4 Body Posture and Handwriting Correlation

While common sense has long identified the existence of a relationship 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. (1998) 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 (2015) 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, Tozadore, Bruno, and Dillenbourg (2024), 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.

3 Automated Body Posture Quality Assessment

3.1 Body Posture Quality Assessment Pipeline

As the literature review highlights, REBA and RULA are widely used, validated standard scales for posture quality assessment. REBA is a systematic measure to evaluate the ergonomic risk factors associated with postures and tasks (Hignett & Mcatamney, 2000). 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 1), 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") (Mcatamney & Corlett, 1993). Like for REBA, the overall RULA score is built as the aggregation of sub-scores, specifically focusing on neck, trunk, legs, upper

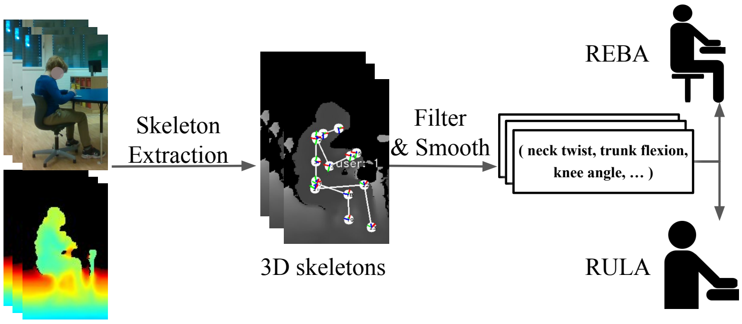


Fig. 2 Automated body posture quality assessment pipeline.

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, which associate a score to different joint configurations[3]. 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 in-the-wild 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 $\alpha = 0.7$); (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.

3.2 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* [4] 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.

[3]Worksheets for the computation of REBA and RULA can be found online at: https://ergo-plus.com/wp-content/uploads/REBA.pdf and https://ergo-plus.com/wp-content/uploads/RULA.pdf
[4]https://nuitrack.com/

4 Experimental Evaluation

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*.

4.1 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 Asselborn et al. (2018) 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.

4.2 Experiment Design

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

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 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.

4.2.1 Experimental Setup

We employed an established Child-Robot Interaction system specifically designed to facilitate handwriting training support (Tozadore et al., 2023; Tozadore, Wang, Marchesi, Bruno, & Dillenbourg, 2022). A social robot was included in the experimental setup, with the purpose of automating the entire interaction. As shown in Fig. 1 - left,

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

the setup includes: (i) an iPad running the *Dynamilis* app, paired with an Apple Pencil, (ii) the social robot QTrobot[5] 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.

4.2.2 Experiment Procedure

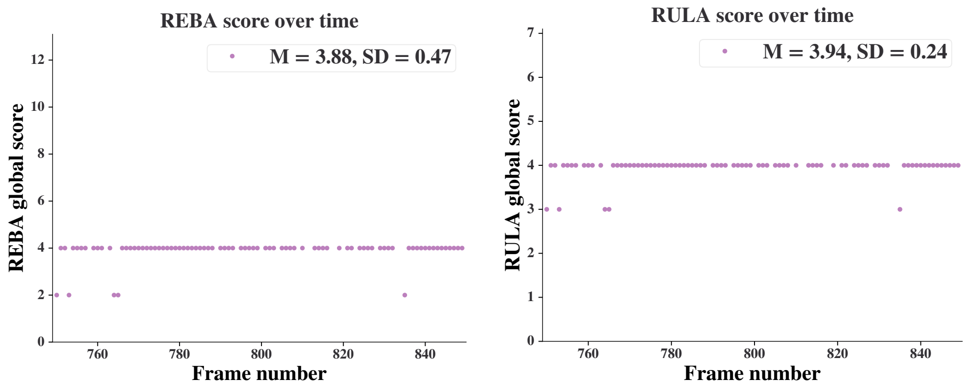
The session unfolds as shown in Fig. 3. At first, a researcher welcomes the child, outlines the structure of the experiment and briefly introduces the robot and the activities in the *Dynamilis* app. The child is also asked to try out the seat and adjust its position and height according to the child's 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[6]. Afterwards, for approx. 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 (Graham & Weintraub, 1996) 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 approx. 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.

4.3 Participants

We invited 31 children (11 girls and 20 boys aged M = 8.52 years old, SD = 0.57) enrolled in two classes of grade three at a local international school to take part in

[5] https://luxai.com/
[6] Test scores, by default settings, are not accessible to children.



(a) (b)

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.

the study [7]. 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.

4.4 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 pipeline described in Section 3. Concretely, we used the out-of-the-box *Nuitrack SDK*[8], 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

[7]This study has received ethical approval from the Human Research Ethics Committee of EPFL under protocol HREC 057-2021

[8]https://nuitrack.com/

the participant (i.e., using the right body joints plus those in the sagittal plane), due to the positioning of the camera.

5 Results

5.1 On the correlation between body posture quality and handwriting quality - 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 Section 5.2. 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.

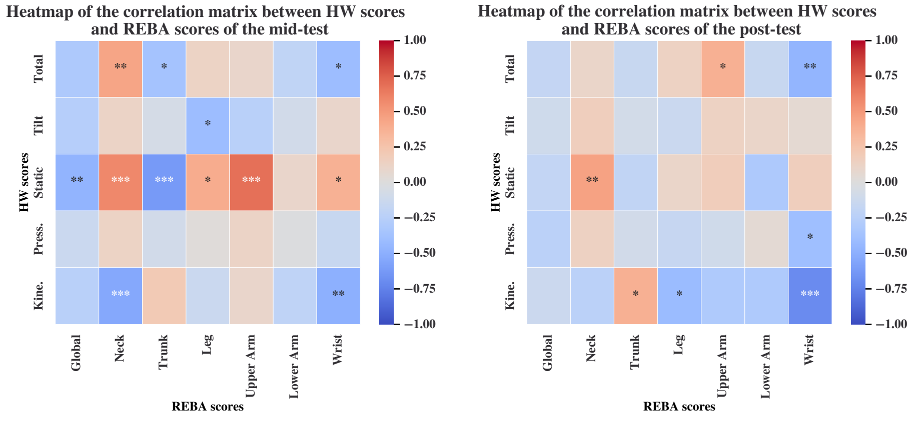
In the correlation heatmap of Fig. 5 negative correlation is represented by the color blue, while positive correlation is marked in red, while stars denote statistical significance. For the mid-test, as Fig. 5a shows, we found a strong significant negative correlation (r <-.4) between:

- HW static score and REBA global score (p <.05),
- HW static score and REBA trunk score (p <.01),
- HW kinematic score and REBA neck score (p <.01),
- HW kinematic and REBA wrist score (p <.05).

While the above results are in line with our hypothesis, others disprove it. Specifically, there was a strong significant positive correlation (r >.4) between:

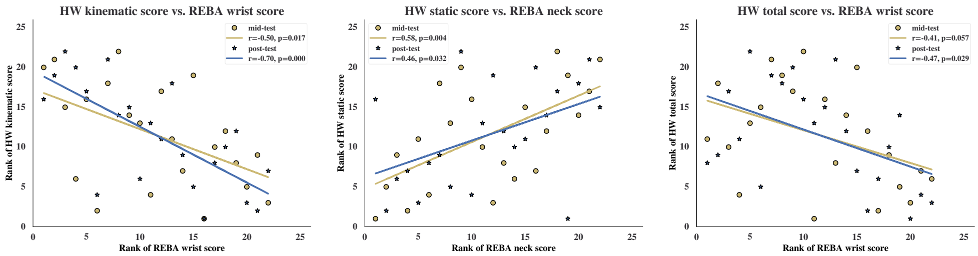
- HW static score and REBA neck score (p <.01),
- HW static score and REBA upper arm score (p <.01).
- HW total score and REBA neck score (p <.05)

To verify the consistency of our findings, as shown in Fig. 5b and Fig. 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=.70, p <1e-3), as well as between the HW total score and REBA wrist score (r=.47, p=.029). Moreover, as in the mid-test, the HW static score and REBA neck score were strongly positively correlated (r=.46, p=.032). 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.



(a) (b)

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: $^*p<.1$, $^{**}p<.05$, $^{***}p<.01$.



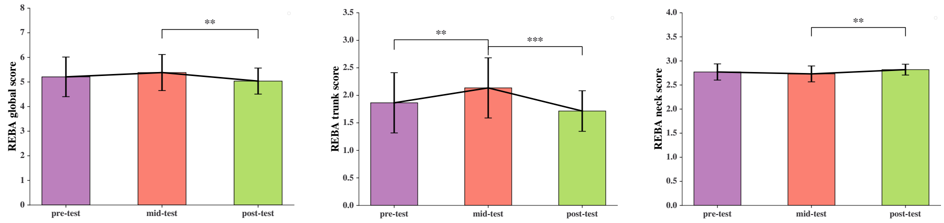
(a) (b) (c)

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.

5.2 On the correlation between body posture quality and handwriting quality - 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 strongly negatively correlated with the HW kinematic score, both in the mid-test (r=-.50, p=.018) and in the post-test (r=-.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=.57, p=.006) and in the post-test (r=.51, p=-.015). Additionally, no



(a) (b) (c)

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 <.1, **p <.05, ***p <.01.

statistically significant correlation found for RULA was in contrast with a statistically significant correlation found for REBA.

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

5.3.1 On body posture quality

Table 1 REBA scores (mean± sd) at pre-test, mid-test and post-test, with T statistics and effect size (*p <.1, **p <.05, ***p <.01)

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	.391	.211	.048**	.208	.937	.036**	.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	.029**	.024**	<1e-3***	.215	.323	.068*	.012**
Cohen-d	0.54	-0.61	0.88	-0.37	-0.28	-0.48	0.48

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 1 and Fig. 7a, comparing the REBA scores between before and after the handwriting training phase, the global score increased from 5.21 to 5.36, but the difference was not statistically significant ($t(26) = 0.87$, $p = .391$, $Cohen\text{-}d = -0.20$). With the sole exception of the neck score, 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, $t(26) = 2.07$, $p = .048$, $Cohen\text{-}d = -0.49$, whose mean value increased by 15%, indicating that children significantly bent their body trunks due to the long handwriting training phase. Similarly, the REBA lower arm score increased by 3% ($t(26) = 2.21$, $p = .036$, $Cohen\text{-}d = -0.41$).

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, ($t(26) = 0.82$, $p = .420$, $Cohen\text{-}d = -0.19$). 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.

5.3.2 On handwriting quality

Table 2 Two-sided Wilcoxon T statistics and effect size on HW scores between pre-test and mid-test

Item	*Total*	*Tilt*	*Static*	*Pressure*	*Kinematic*
W stat.	133.0	162.0	150.0	158.0	119.0
p val.	.442	.999	.751	.916	.252
Cohen-d	-0.22	-0.11	-0.13	-0.08	0.16

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 (Asselborn et al., 2021). As shown in Table 2 and Table 3, 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 (K. Feder & OT(C, 2007) thus not significantly affected by a 15-minutes handwriting training.

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

5.4.1 On body posture quality

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.

As shown in Table 1, a statistically significant difference was found on the REBA global score, $t(26) = 2.31$, $p = .029$, whose mean value decreased from 5.36 to 5.01

with medium effect size ($Cohen\text{-}d = 0.54$). 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, ($t(26) = 3.81$, $p < 1e-3$, $Cohen\text{-}d = 0.88$), and the wrist score, which dropped from 1.08 to 1.06, ($t(26) = 2.69$, $p = .012$). Conversely, there was a significant increase in the neck score after the posture intervention ($t(26) = 2.39$, $p = .024$), with medium effect size ($Cohen\text{-}d =$ -0.61). 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, ($t(26) = 1.23$, $p = .229$, $Cohen\text{-}d = 0.30$). 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 ($t(26) = 2.87$, $p = .008$), while the neck score increased from 3.61 to 3.75 ($t(26) = 2.39$, $p = .024 < .05$).

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

5.4.2 On handwriting quality

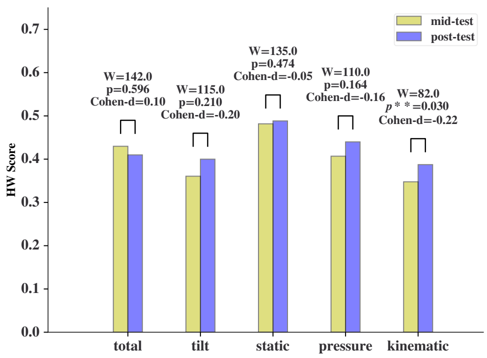


Fig. 8 Comparison between the HW scores at the mid-test and post-test with Wilcoxon T test.

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 3 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 ($W = 82.0$, $p = .030$). 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.

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

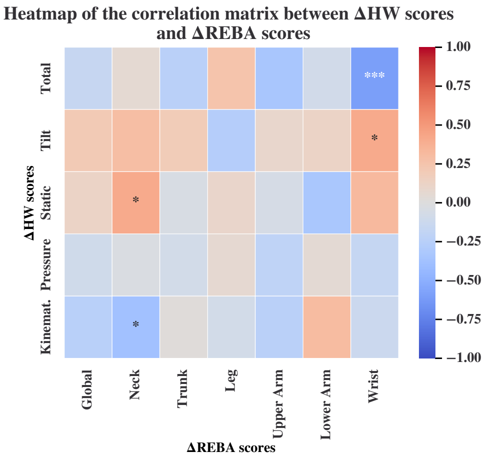


Fig. 9 The heatmap of the Spearman correlation matrix between the mid-post change of HW scores and the mid-post change of REBA scores. The value of the correlation coefficient r is encoded by the color while the corresponding p value is reported with the asterisks convention: *p <.1, **p <.05, ***p <.01.

As a follow-up on the previous analysis, we also checked whether variations in body posture quality, from the mid-test to the post-test, are correlated with variations in handwriting quality. The results of the two-sided Spearman's rank correlation between REBA and HW scores is 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. Moreover, a marginally significant moderate negative correlation was found between ΔHW kinematic score and ΔREBA neck score (r=-.38, .05< p <.1). Lastly, marginally significant strongly positive correlations were found between ΔHW tilt score and ΔREBA wrist score, and between ΔHW static score and ΔREBA neck score (r >.40, .05< p <.1).

Table 3 HW scores (mean± sd) at pre-test, mid-test and post-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

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 =-.41, p = .056).

6 Discussion

6.1 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 in Sections 5.1 and 5.2. As shown in Fig. 6a, we found a statistically significant strong negative correlation between the HW kinematic score and REBA wrist score, which means that the pose of the wrist is strongly related to pen dynamics during writing (e.g., the handwriting speed (Asselborn et al., 2018)). Specifically, the REBA/RULA wrist score mainly measures the wrist flexion (Hignett & Mcatamney, 2000; Mcatamney & Corlett, 1993), 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 (Lee & Sechachalam, 2016), gripping strength (Lee & Sechachalam, 2016), and hand dexterity (Metcalf et al., 2014). 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. In addition, as shown in Fig. 6b, it was noticed that the angle of neck flexion of the children is strongly correlated with the HW static score, 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.

6.2 The variation of handwriting body posture of children

In the experiment, the body posture of the children was evaluated during three handwriting tests at different moments of the experiment, as described in Section 4.2.2. At the pre-test, the children were in their initial body postures, which were developed from their past personal and educational experience and might be influenced by their mental and physical states when starting the experiment. After the approx. 15-minutes long handwriting training phase, we assume the children fell into their daily, more natural and comfortable handwriting body posture due to the increasing engagement, familiarity with the experiment set-ups or fatigues. Regardless of the cause, the change in posture is testified by the significant increase in the trunk score between the pre-test and mid-test, as shown in Fig. 7b. The body posture correction intervention also had an impact on the children's body posture, whose significance was revealed by the Student's T test as shown in Table 1 (see part *Mid-test vs. Post-test*). Thus, we argue that the dynamics of body posture play an important role in the educational context: our study reveals how the children's posture changed already after 15 minutes of activity, and how a posture-related intervention has a direct impact on their activity (handwriting quality), which means that the body posture is not only an indicator but also a lever for learning-supporting interventions.

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 ($t(26) = 2.77$, $p = .010$, $Cohen\text{-}d = -0.68$). Thereby a conclusion cannot be drawn with regard to whether the children's initial body postures is already close to the correct body posture.

6.3 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. As mentioned in Section 2.3, 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.

6.4 Limitations and Future Work

While our work sheds new light on the relationship between handwriting and body posture quality, 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.

7 Suggestions on the design of CCI system for handwriting training support

In this study, correlations on multiple pairs of postural elements and handwriting dimensions were identified as described in Section 5.1 and 5.2. 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.

The experimental system described in Section 4.2.1, 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 (Smits-Engelsman et al., 2001)) 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.

8 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 of one's body posture and their handwriting, 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 body posture quality and handwriting quality, 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 strongly 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.

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