Factors Affecting the Clarity of Non-Dominant Handwriting versus Dominant Handwriting

Andrew Trotman[1*], Matt Tyler[1], Hayden McAlister[1], Chris Button[2], Lech Szymanski[1]

[1]School of Computing, University of Otago, Dunedin, New Zealand.
[1]School of Physical Education, Sport and Exercise Sciences, University of Otago, Dunedin, New Zealand.

*Corresponding author(s). E-mail(s): andrew.trotman@otago.ac.nz;
Contributing authors: matt@fernve.com; mcaha814@student.otago.ac.nz; chris.button@otago.ac.nz; lech.szymanski@otago.ac.nz;

Abstract

We are interested in shifting writing from the dominant hand to the non-dominant hand in adults that suffer from Repetitive Strain Injuries (RSI) or stroke. Anecdotally, some adults can already write on a whiteboard using their non-dominant hand. In this investigation we examine three factors that differ between dominant writing on paper and non-dominant writing on a whiteboard: orientation of the writing surface (horizontal or vertical), grip size (pen-size or marker-size), and handedness (dominant or non-dominant). We asked 180 members of the public to write the same short phrase in all 8 configurations and to rank their writing from clearest to least clear. We then manually assessed the 1440 samples for clarity. Our analysis shows that the significant factors affecting clarity are the hand used for writing, and the orientation of the surface, while grip size does not affect clarity. We also find that although writing clearly with the non-dominant hand on a vertical surface with a marker is not a universal trait, 14 of our 24 (58%) left-handed writers possess this skill, but no right-handed writers do.

Keywords: Handwriting; Adaptation; Handedness; Pen-grip; Orientation.

1 Introduction

Despite the widespread adoption of computers for communications, handwriting has not become obsolete. Indeed, handwriting continues to be used to take phone messages, to fill out forms, teaching on a whiteboard, and so on [1]. But some people are restricted by injury and cannot write. For example, Garnett et al. [2] estimate that 9% of the US adults suffer from Repetitive Strain Injuries (RSI) in a given 3 month period, debilitating injuries such as strokes also affect an individual's ability to write.

Unfortunately, there are no effective medical interventions for RSI. The best medical advice is to avoid use. In practice *avoid use* isn't very helpful in the case of writing because there is often no alternative. We are interested in tackling this problem head on. That is, our work is driven by the research question: *what can be done to enable patients to write when their dominant hand becomes incapacitated?*

Serendipitously we observed an individual writing, in English, on a whiteboard with a whiteboard marker using their non-dominant hand. That writing was almost as clear as writing with their dominant hand. It was not clear whether that individual was ambidextrous, or whether non-dominant writing on a whiteboard is a universal trait. It was clear that if this ability is universal, or can be learned, then it might be leveraged as a medical intervention for patients who lose the ability to use their dominant hand, either through RSI or otherwise.

Our observation leads to the research questions we study herein: *Is the ability to write clearly on a vertical surface with the non-dominant hand a universal trait*? This question can be further broken down in the research question: *How do the different factors affect the clarity of the writing*?

There are several factors that are fundamentally different between writing on paper with a pen and writing on a whiteboard with a marker. In this investigation we study three of these factors to determine which, if any, affect the clarity of handwriting. The factors are: the orientation of the surface (vertical or horizontal), the grip-size (pen or marker sized), and the hand used in the writing (dominant or non-dominant). To do this we asked 180 individuals to write the palindrome "step on no pets" in all 8 possible combinations, and then analysed the effect of each factor on the clarity of their writing. To determine clarity we asked the participants to rank their 8 samples in order from most clear to least clear. Separately we asked 3 assessors to rank all 1440 samples from most clear to least clear.

In this paper we report on this experiment. Our data is publicly available.[1] We find there is a statistically significant difference between the average score for samples given by the dominant and non-dominant hand and between orientation. We do not find a statistically significant difference between grip sizes. We note some interesting behaviours of outliers suggesting a small subset of the population may be more receptive to some factors than the entire population. We also investigate the effect size of each factor on clarity, finding a significant contribution at the 1% level for all factors.

2 Related Work

The fact that healthy humans typically display uniformity in outcome despite potentially using different muscle groups (i.e., limbs) is known as motor equivalence. 'Hand' writing is a good example of motor equivalence as characteristics of our writing are common and identifiable even when quite different configurations of limbs are used to produce text. Indeed, Raibert [3] showed that with some practice people could write a simple palindrome ("Able was I ere I saw Elba") reasonably consistently with their dominant wrist braced, a non-dominant hand, a pen held between their toes, or even their teeth. Motor equivalence is of theoretical significance because it implies that actions are represented in the central nervous system in more abstract terms than as commands to specific muscles or limbs [4]. For example, the groups of fine movements required to produce a sequence of letters may be represented in relative terms as 'strokes' of relative positions and configurations against which the specific writing instrument and medium are scaled during motor output [5].

Despite unilateral hand dominance developing in most humans at around 10-12 months of age and persisting into late adulthood [6], we remain capable of using either limb for complex tasks like handwriting. For the large majority of us adapting to changes in limb, writing implements, medium (paper vs. digital screen), or orientation (vertical vs. horizontal) can be achieved with practice [7]. Indeed, for roughly 3% of the population that are ambidextrous, they can write with either hand equally well [8]. How this simple but remarkable feat of human coordination is achieved is a question worthy of further investigation.

We start this further investigation by determining how clearly the general population can already write with their non-dominant hand, and which factors affect the clarity of that writing.

There is considerable prior work on clarity. Graham [9], for example, notes that clarity is affected by more than just the formation of letters, it is influenced by graphic, syntactic, and semantic information within the sample.

There are also many different metrics used to score handwriting clarity, most of which focuses on early intervention for dysgraphic children. For the Latin alphabet, there is the Detailed Assessment of Speed of Handwriting (DASH); the Ajuriaguerra scale (E scale); and the Concise Evaluation Scale for Children's Handwriting (BHK), the French gold-standard for diagnosing dysgraphia [10]. The scoring is typically performed by trained experts, making these metrics largely inaccessible to us. Some work has examined the use of Neural Networks to diagnose dysgraphia [11].

But the focus of this study is factors that affect clarity in healthy individuals, not dysgraphia. To achieve this we create a rank ordering of 1440 handwriting samples – and from that analyse which factors result in clearer writing.

[1] https://doi.org/10.5281/zenodo.11515462

Creating rank orders of many items through pairwise comparison has recently been examined by Seifikar et al. [12]. Their tool, JUDGO, presents two documents to a human assessor, who is asked to identify the better of the two (or to identify that they are equivalent). It keeps track of the best document, choosing one new document to compare to in each round. Eventually it must break ties and it does so in a way that maintains previous decisions. JUDGO produces a ranked list of equivalence classes – groups of documents that are judged equal. Seifikar et al. claim their approach requires fewer comparisons than the naive approach, which is essentially an insertion sort[2]. We implemented the algorithms of Seifikar et al. in our own assessment tool.

Our motivating question *what can be done to enable patients to write when their dominant hand becomes incapacitated?* has been studied in a military setting where amputations and crushing injuries are seen. That work includes the *Handwriting for Heroes* program [13], a workbook of pen-use exercises to train the non-dominant hand to write. A small study of 5 non-impaired individuals suggests that the six-week program is effective [14], with participants improving one grade level in writing speed and most participants improving in legibility in the time period. Other non-military studies support this finding. Sandve et al. [15] experimented with 9 strong right-handed people who wrote, with their left hand, the same 114 words per day for 15 consecutive days. They found that this was sufficient training for right-handed people to learn to write legibly with their left hand. Walker & Henneberg [16] experimented with 21 individuals, and 2 sentences over 28 days, and found much the same, concluding that the dominance of one hand over the other might stem from small biological or social differences, and might not be predetermined.

It is clear from these studies, and others [17], that humans are able to transfer writing from the dominant to the non-dominant hand with very little training – more specifically, horizontal writing on paper with a pen. However, the quality of the writing is not high. Marcori et al. [18], in their survey on changing handedness, observe a general trend that those who have transferred writing from one hand to the other do not reach the level of mastery as those for whom writing with the target hand is preferred. They also observe that continual practice is needed, as is the pressure to practice.

In contrast to this prior work, we are looking for factors that affect the clarity of writing, factors that might be exploited when a shift of hand is necessary.

3 Methods

We used one iPad (iPad 12.9" 5^{th} generation model MHNK3X/A running iOS 16.1.1) and one Apple Pencil (Apple Pencil 2 Model A205 hardware version 1100, Firmware Version: 0154.0093.0444.0060) to collect the handwriting samples electronically. This required both custom hardware and software.

Hand	Orientation	Grip
Right	Horizontal	Pen
Right	Horizontal	Marker
Right	Vertical	Pen
Right	Vertical	Marker
Left	Horizontal	Pen
Left	Horizontal	Marker
Left	Vertical	Pen
Left	Vertical	Marker

Table 1: The 8 configurations of the 3 parameters.

3.1 Hardware

There are 8 possible configurations of the 3 parameters we are studying, as shown in Table 1. Custom hardware was needed in order to collect samples from 6 of these – those using either the marker grip or in the vertical orientation.

The pencil has a grip similar to that of a pen, but not of a white-board marker. To generate a marker-sized grip we took an old marker and drilled out the nib, creating an empty chassis. As the marker was shorter than the pencil, we took a second marker and attached that to the end – thus extending the length

[2]https://en.wikipedia.org/wiki/Insertion_sort

Fig. 1: Apple Pencils in the pen configuration 9 mm x 166 mm (top) and marker configuration 16 mm x 183 mm (bottom).

of the grip to the length of the pencil. A cap was used to prevent the pencil from sliding in the chassis. A simple piece of string attached to the cap was used to remove it and so that the pencil could easily be inserted and removed. In this way the same pencil was used in both the pen and marker configurations (as shown in Figure 1).

Using the iPad in the horizontal orientation was straightforward. For the vertical orientation we custom-built a mounting bracket using an easel mounted on a tripod. We ensured no slack so that the iPad would not flop about while being used. Before the experiment began we calibrated the height of iPad with the height of the participant – which we achieved by setting the top of the easel a fixed distance from the top of the participants head. This was achieved using a ruler as a leveling device (as shown in Figure 2).

The right and left handed data collection required no additional hardware.

3.2 Software

We built software to collect all 8 samples from an individual. That software starts by collecting demographic details from the user including: Sex, age, writing hand, handedness, how frequently the participant writes and uses a stylus, and their level of education. We asked about handedness separately from writing hand because some left-handed people are taught to write with their right hand (known as force-handedness). The demographics collection screen is show in Figure 3.

In order to reduce follow-on effects, each participant was given a unique ID and that ID was used as a index into a balanced Latin square. That is, the order in which the 8 samples were collected differed from one participant to the next. The software stated the three factors, then one of the authors configured the hardware. The participant then wrote in the space provided (see Figure 4). This was repeated for each of the 8 samples. The sampling rate of the stylus was 240 Hz.

Finally, the participant was asked to rank their writing samples from most clear to least clear by dragging the samples into the correct order (see Figure 5).

3.3 Data collection

Ethical approval was granted by the University of Otago Human Ethics Committee, reference number D23/232. Participants were adults over the age of 18, and were required to signed a consent form.

We conducted the experiment in a local student recreational area that contained a cafe. We offered a $10 campus-cafe voucher for anyone (student or otherwise) who would complete our experiment. Participants could withdraw at any time without penalty, but forfeited the voucher if they did.

First we calibrated the orientation of the iPad with the edge of the table – so that we could determine whether the participant rotated the writing surface. We leave for future work the analysis of this

Fig. 2: The vertical orientation. The ruler is aligned with the top of the participant's head thus placing the surface at the same height relative to the participant. In this case, the individual is an author of the paper.

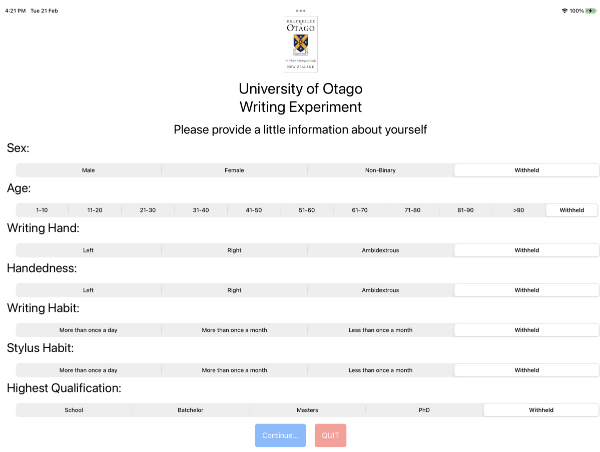


Fig. 3: The demographics screen used to collect detail from the user.

measurement – anecdotally, some left-handed writers rotate paper to avoid smudging, but exploring this is beyond the scope of this paper.

Next we adjusted the height of the tripod using the technique illustrated in Figure 2.

Then our software collected the participant's demographics and the 8 handwriting samples. Participants were not given the opportunity to practice before their writing samples were collected.

So that we could compare like-to-like we asked all participants to write the same short sentence. In order to remove factors due to letter ordering we followed the example of Raibert [3] and used a palindrome. Raibert [3] used "Able was I ere I saw Elba", which, in preliminary experiments, was neither

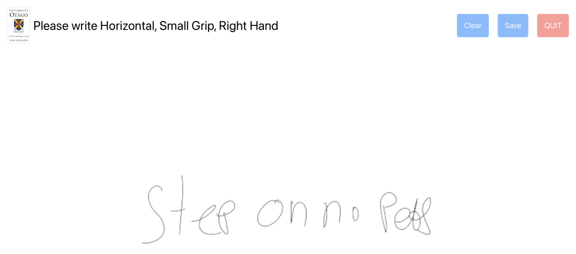


Fig. 4: An author configured the experiment according to the Latin square, then the participant wrote in the space available.

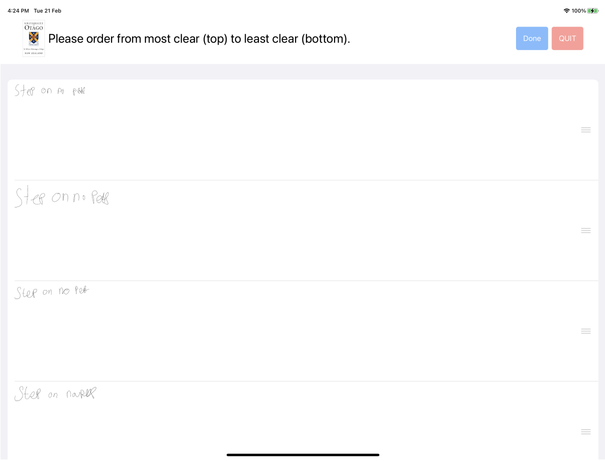


Fig. 5: Participants used this screen to order their writing samples from most clear to least clear.

memorable nor short enough to fit on one line of the iPad – and so we used "step on no pets" which is both memorable and short enough to fit.

The participants were not given any instruction on how quickly to write, and the writing size was not specified. That is, we just asked the participants to write the sentence in the given configuration. While such instructions can affect behaviour (and therefore experimental outcome), we were careful to not give instruction that might do so. We wanted the participant to write as they normally would.

In the final stage of data collection the participant ranked their writing samples from most clear to least clear. We did not provide a precise definition of clear, instead relying on the judgment of the participant – who was not given details of which samples were from which combination of factors.

3.4 Data analysis

At the end of the data collection stage we had 8 samples from 180 participants, totaling 1440 samples. We had the demographics of the participant, and we had the relative ordering *for each participant*. However we did not have a total ordering over all 1440 samples – something we will use in future work in which we intend to gamify the process of teaching children to write and for rehabilitation of RSI and stroke patients.

To generate a total ordering we built assessment software similar to JUDGO [12], but for images of writing samples. This software, Pairwisely, starts with a quick tutorial of the assessment process. It then presents two writing samples to an assessor who chooses the clearest, or marks that they are equally clear

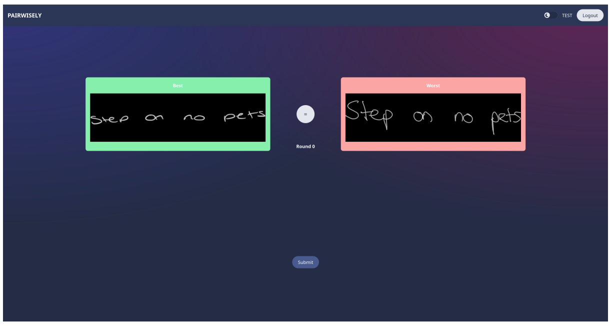


Fig. 6: Pairwisely, the software used by the assessors to create the total ordering of the clarity of writing samples. The assessor could choose the left, right, or mark that they are equally clear.

(see Figure 6) – immediate feedback was given by setting the colour of the clearest to green and the least clear to red.

We chose to assess each of the 8 categories of samples independently in an effort to reduce assessor fatigue. Once all 8 categories had been assessed a second stage of assessment was used to merge the equivalence classes into a total ordering for that assessor. We asked 3 assessors to assessed the entire set, and separately asked 2 further assessors to assess the same single category twice.

Assessors were chosen from the Information Retrieval Lab at the University of Otago. The three assessors included two 300-level undergraduate students (including one author of this paper), and a 400-level student. The two assessors were both 300-level undergraduate students.

To get some indication of the robustness of the judgments made by each assessor (assessor self-agreement) we took the total ordering generated by each of the 2 assessors and sorted them into 8 equal sized buckets. We then ran an ANOVA and computed ICC3 [19] over those buckets. Note that this technique assumes categorical data but we have continuous data and so it is reasonable to assume a level of disagreement at the bucket boundaries. We then performed the same bucketing on the 3 assessors and computed the same ICC3 score. We performed the same technique for cross-assessor agreement of the 3 assessors.

Age	**11-20**	**21-30**	**31-40**	**41-50**	**51-60**	**61-70**	**71-80**
Participants	94	81	2	0	1	1	1

Table 2: The breakdown of participants by age. We only sampled adults, so the 11-20 age group is, more precisely, 18-20

4 Results

4.1 Demographics

Our participants were individuals (adults over the age of 18) on the campus of the University of Otago and as such are not representative of the general population, but are representative of the population in the area. The breakdown by age is show in Table 2, from where it can be seen that most participants (94 of 180) are aged between 11 and 20[3] (i.e. undergraduate students) and most of the remainder (81 of 180) are aged between 21 and 30 (i.e. final year students and postgraduate students). While our age distribution is skewed, we do not believe that this skew affects the final results – but we are aware that this sample is not as experienced with a pen as some older members of the public might be.

The sex breakdown is shown in Table 3 along with the statistics published by our institute [20]. It is clear from the table that the sample is representative of the student population (our population being: 39% male, 62% female, and 1% non binary). Also inline with the student population is our breakdown of education level shown in Table 4. Our numbers are expected to vary slightly from the institutional values because we ask the highest level of education but the institute reports the number of students studying at each level. We chose to differ so that we could include members of the public rather than just

[3] More accurately, 18-20 as we required participants to be adults over the age of 18.

Sex	Male	Female	Non-Binary	Withheld
Participants	68	109	1	2
Proportion	38%	61%	1%	1%
Institutional Proportion in 2022	39%	61%	0%	Not Reported

Table 3: The breakdown of participants by sex.

Qualifications	School	Bachelor	Masters	Withheld
Participants	149	27	3	1
Proportion	83%	15%	2%	1%
Institutional Proportion in 2022	78%	15%	7%	Not Reported

Table 4: The breakdown of participants by highest qualification.

Hand	Right	Ambidextrous	Left
de Kovel et al. [21]	90%	1%	10%
Handedness	153	7	20
Proportion	85%	4%	11%
Writing Hand	155	1	24
Proportion	86%	1%	13%

Table 5: The breakdown of participants by handedness.

students. 83% of our participants had completed school, 15% had completed a Bachelor's degree, 2% had completed a Master's degree and 1% withheld the information.

de Kovel et al. [21] report that in their UK study of approximately 500,000 people, 90% are right handed, 1% are ambidextrous and 10% are left handed. The numbers differ from country to country, with 6.8% outside the UK being left handed. The breakdown of handedness and preferred writing hand is shown in Table 5. Our numbers (85% right, 4% ambidextrous, and 11% left) are inline with those of de Kovel et al. In our sample of 180 participants, 9 state that they write with their non-dexterous hand. Of those, 5 are ambidextrous and write with their left hand, 1 is ambidextrous and writes with their right hand, 2 are left handed and write with their right hand, and one is right handed and writes with their left. It is tempting to claim these participants are forced-handers but the numbers are too small to draw any conclusions – see Vuoksimaa et al. [22] for statistics on forced handedness.

Table 6 presents the frequency at which the participants write and write with a stylus. It is not surprising that most of our participants write daily (122 of 180), but it is surprising that some self-report writing less frequently than once a month (4 of 180). Our population is mostly students, and our results appear to demonstrate a slow adoption of stylus writing in this group with only 31 reporting daily use and 20 monthly use.

In this section we have shown that our sample does not show the same age breakdown as the general public. But, it does appear to be representative of the student cohort at our institute. The sex breakdown and educational level also match that at our institute. The handedness matches that of the general public. We can expect the use of writing to be higher than the general public because, as students, we can expect note taking during lectures to be common practice. Given the age demographic it is surprising that electronic styluses are not well adopted.

4.2 Writing

In total 180 participants provided 8 writing samples each. As part of anonymising the data, each participant was issued a UUID (Universal Unique Identifier) and we key each sample on that UUID. Each sample is a recording of the path of the stylus. Each path includes one or more strokes (a stylus-down, stylus-move, stylus-up event). Each stroke consisted of one or more movements. At each movement we recorded the stylus location, the time, the opacity, azimuth, force, and altitude from the surface.

From this data we reconstruct the original writing of the participant. Figure 7 shows the eight writing samples from a right handed male participant aged between 11 and 20 whose highest qualification is high school level (a typical undergraduate student at our institute). From visual inspection it is clear that, for this individual, the right-handed writing is clearer than the left and that when the left hand is used the vertical surface writing is clearer than the horizontal surface.

Frequency	More than daily	More than monthly	Less than monthly	Withheld
Writing	122	54	4	0
Stylus Use	31	20	112	17

Table 6: The breakdown of participants by writing frequency.

Fig. 7: Eight writing samples from a single participant demonstrating that the clarity of the writing differs depending on the orientation of the surface, the hand used in writing, and the size of the grip. This individual was chosen by averaging (over the 8 samples) the average sample scores, then taking the median participant.

	ICC	p-value	95% Confidence Interval
Unbucketed ICC3	0.540	0.0	$[0.51, 0.57]$
Bucketed ICC3	0.541	0.0	$[0.51, 0.57]$
Unbucketed ICC3k	0.779	0.0	$[0.76, 0.8]$
Bucketed ICC3k	0.780	0.0	$[0.76, 0.8]$

Table 7: Inter-class Correlation Coefficients for all three raters across all 1440 samples. ICC3 measures the agreement of these raters while ICC3k averages the rater scores first, leading to higher reliability.

We also measured the cross-assessor agreement between the 3 assessors who assessed all 1440 samples. The results are reported in Table 7 which shows fair, but not good, inter-class correlation coefficients for ICC3, and excellent coefficients for ICC3k [23]. This is despite the fact we have applied the technique to continuous data that we are treating as categorical. We also observe only a very small increase in coefficient values when bucketing the data, indicating that this step may be unnecessary.

4.3 Factors affecting clarity

In this section we account for left-handed and right-handed individuals by processing the data on the bases of dominant and non-dominant hand. That is, a left-handed writer's left handed writing is considered alongside a right-handed writer's right handed writing as having been written with the dominant hand. A left-handed writer's right handed writing and a right-handed writer's left handed writing is considered non-dominant. Of the 7 ambidextrous participants, 6 wrote with only 1 hand only, 1 stated that they wrote with both hands. That 1 individual was considered to always be writing non-dominantly – while this is arbitrary, it is only 0.6% of the participants.

Factor	Mean
Dominant-handed†	2.626
Non-dominant-handed	6.354
Horizontal†	4.292
Vertical	4.708
Pen Grip	4.469
Marker grip	4.531

Table 8: Mean scores for each factor being tested. Significance at 1% is shown with a dagger: †.

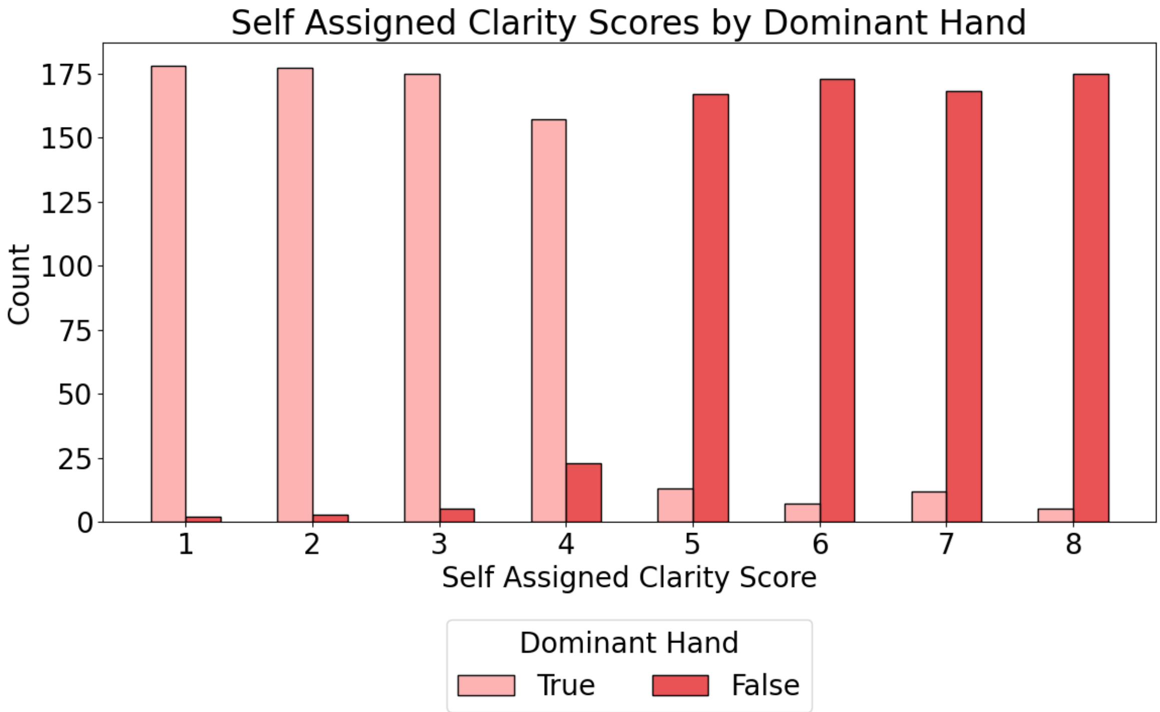


Fig. 8: Distribution of self-assigned clarity scores showing that writing with the dominant hand is substantially clearer than with the non-dominant hand. 1 is the clearest and 8 least clear.

4.3.1 Individual factors

Each participant ranked their writing samples from most clear to least clear – and we assigned a score of 1 to 8 to the samples where 1 is most clear and 8 least clear. We computed the mean scores for each factor we were testing (see Table 8). Significance was tested using unpaired 2-tailed t-tests.

We separated the dominant samples from the non-dominant samples and plot the two distributions in Figure 8. The mean self-assigned clarity score for dominant writing was 2.626 and for non-dominant writing it was 6.354. A 2-tailed t-test produced a p=0.000. That is, writing with the dominant hand is significantly clearer than writing with the non-dominant hand regardless of the other factors.

Figure 9 shows the distribution of scores when only the orientation of the surface is taken into account. The mean horizontal self-assigned clarity score was 4.291, but for vertical it was 4.708, p=0.001. To our surprise, writing on a horizontal surface is clearer than writing on a vertical surface.

Figure 10 shows the distributions for the two grip sizes. Mean marker self-assigned clarity score = 4.530, mean pen score = 4.469, p=0.613. That is, the pen grip size makes no statistically significant difference to the self-assigned clarity of the writing.

These results show that, at least for an individual, the hand used to write and the orientation of the surface affect the clarity of the writing, but that pen grip does not. This latter observation is surprising as the use of a larger pen grip is a commonly suggested remedy for those suffering from RSI [24], and

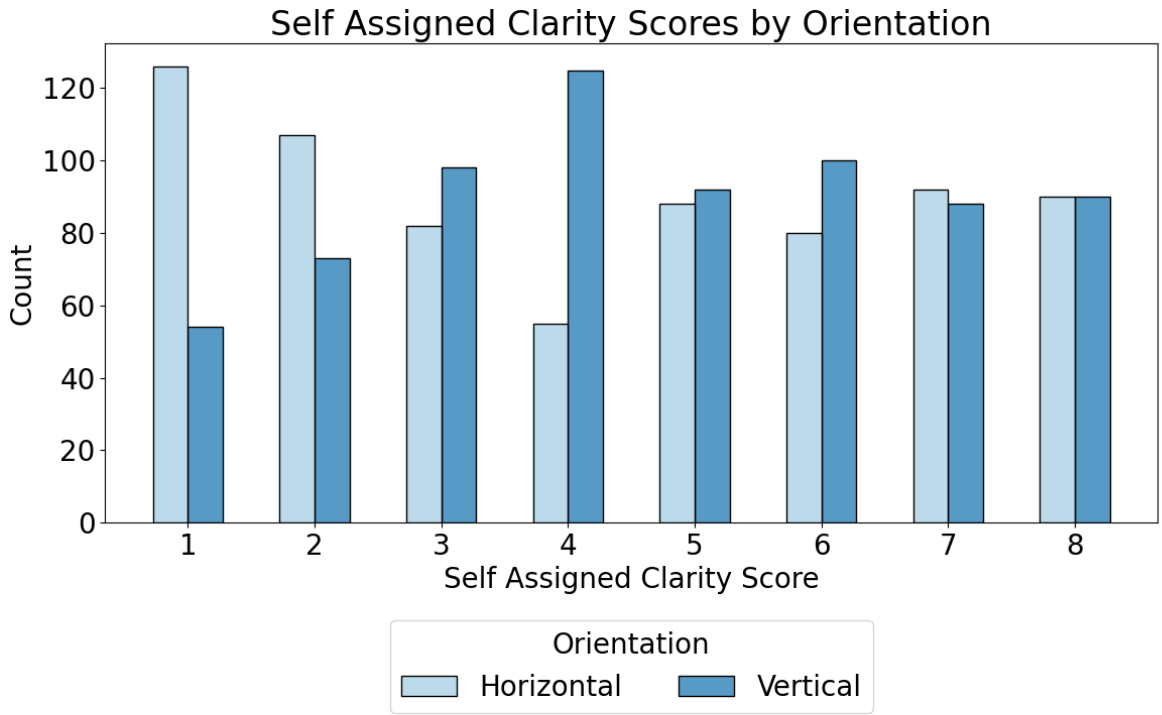


Fig. 9: Distribution of self-assigned clarity scores showing that writing on a horizontal surface is clearer than writing on a vertical surface. 1 is the clearest and 8 least clear.

especially so since Wu & Luo [25] found that the error rate when using medium sized grips (8 mm or 11 mm) was lower then when using a small (5.5 mm) or large grip (15 mm). Our pen had a 9 mm diameter and our marker had a 16 mm diameter.

4.4 Clarity

The previous section analysed the factors affecting the clarity of writing of an individual. In this section we analyse the relative clarity of writing. That is, although we know that the handedness of the writing affects clarity, we don't know whether one participant's clear is another participant's unclear.

To address this question we used the total ordering of the samples generated by the three assessors who assessed all samples using Pairwisely. Each user of Pairwisely generated a ranked order of equivalence classes, but the number of equivalence classes is assessor dependent (188, 176, and 1059 respectively).

We use a set of assessors to determine the clarify of the handwriting samples. To ensure that the ratings are meaningful we need to know that the assessors agree with with each other. To measure this we employ the Intra-class Correlation Coefficient, ICC, a common measure of the reliability of assessors. There are several varieties of ICC, but our work requires only ICC3 and ICC3k. ICC3 measures a set of fixed assessors, i.e. we are not aiming to generalize beyond these assessors to some hypothetical larger population of assessors, we only want to measure the agreement of the assessors we have. ICC3k is similar, but also accounts for the number of assessors. ICC3k can give a more accurate statistic when considering the number of assessors, however we find the effect is minimal.

We check assessor agreement not only with the normalized scores, but also with bucketed scores. The motivation for this is clear: two assessors may not agree exactly on where a particular handwriting sample may lie on a continuum, but they may be more likely to agree it lies in some discrete region of the continuum. The edges of these buckets still give rise to the possibility of disagreements.

After the assessors completed the assessment process we bucketed the total ordering into 8 equal-sized buckets and we ran the ANOVA to compute the ICC3 of the 2 assessors who each assessed one of the modalities more than once. Assessor 1 double assessed right handed writing with a pen on a

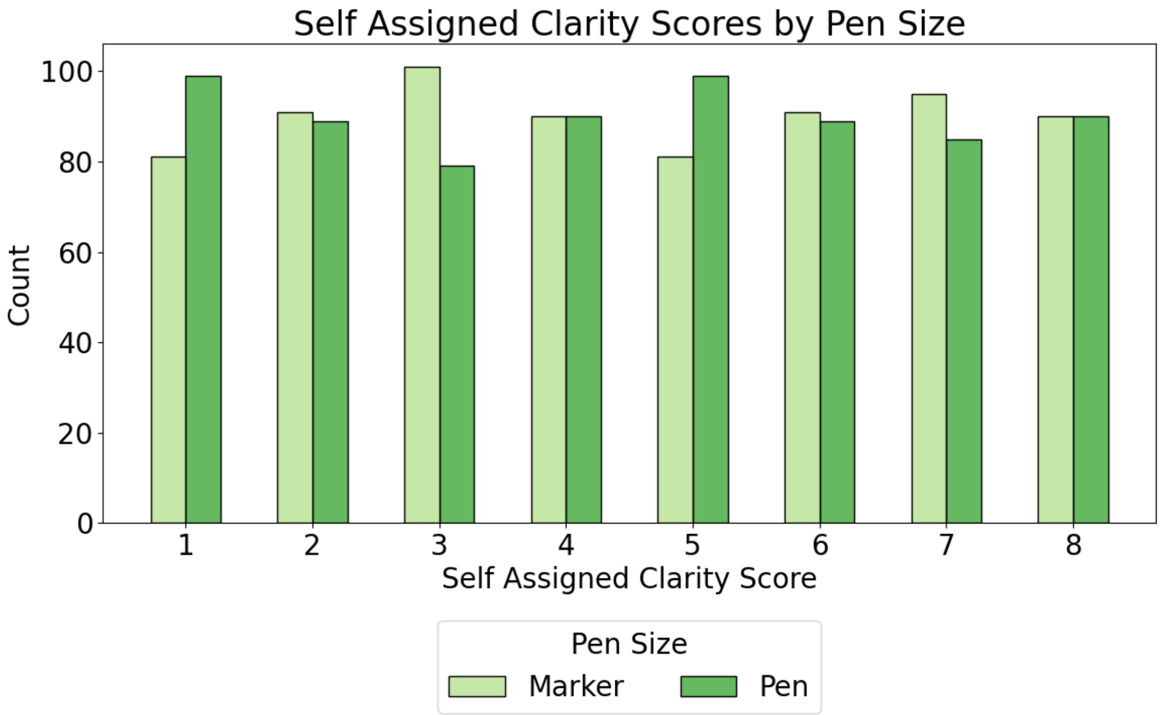


Fig. 10: Distribution of self-assigned clarity scores showing that grip size does not affect clarity of writing. 1 is the clearest and 8 least clear.

vertical surface and achieved a consistency of ICC3=0.8127 (p=0). Assessor 2 double assessed left handed writing with a pen on a vertical surface, and their consistency was ICC3=0.8269 (p=0). From this we can reasonably conclude that assessors have an excellent level of consistency – that is, the assessors are performing reliably.

We normalised the scores from each assessor by numbering each equivalence class with its rank order, then linearly scaling into the range 0 to 1. This way each hand writing sample is given an assessor specific score between 0 and 1 and all samples in the same equivalence class have the same score. An average score for each sample was computed over the 3 assessor scores.

Assessor	Classes	Mean	Standard Deviation	Shapiro-Wilk p-Value
0	188	0.465	0.281	1.56×10^{-22}
1	176	0.579	0.291	2.39×10^{-26}
2	1059	0.528	0.293	4.84×10^{-24}
Average	N/A	0.524	0.240	6.10×10^{-26}

Table 9: Statistics of the equivalence classes and scores of each assessor. The p-value is computed using the Shapiro-Wilk test for normally distributed data.

Figure 11 shows the distribution of scores for each assessor alongside the rater's average score and the middle 50% of the scores. Jitter has been used in columns simply as a way of indicating density, and is otherwise meaningless. It is clear from visual inspection that the assessors are generating an effective rank ordering (i.e. the distribution is not clumped). Table 9 presents, for each assessor, the number of equivalence classes they generated, the mean, and the standard deviation of the score alongside the p-value from the Shapiro-Wilk test for normally distributed data. A p-value of less that 0.05 allows us to reject the null hypothesis that the data is normally distributed (i.e. it is not normally distributed). This is not surprising since the data is generated from a linear numbering of each sample, but it does affect which statistical tests can be performed on the data.

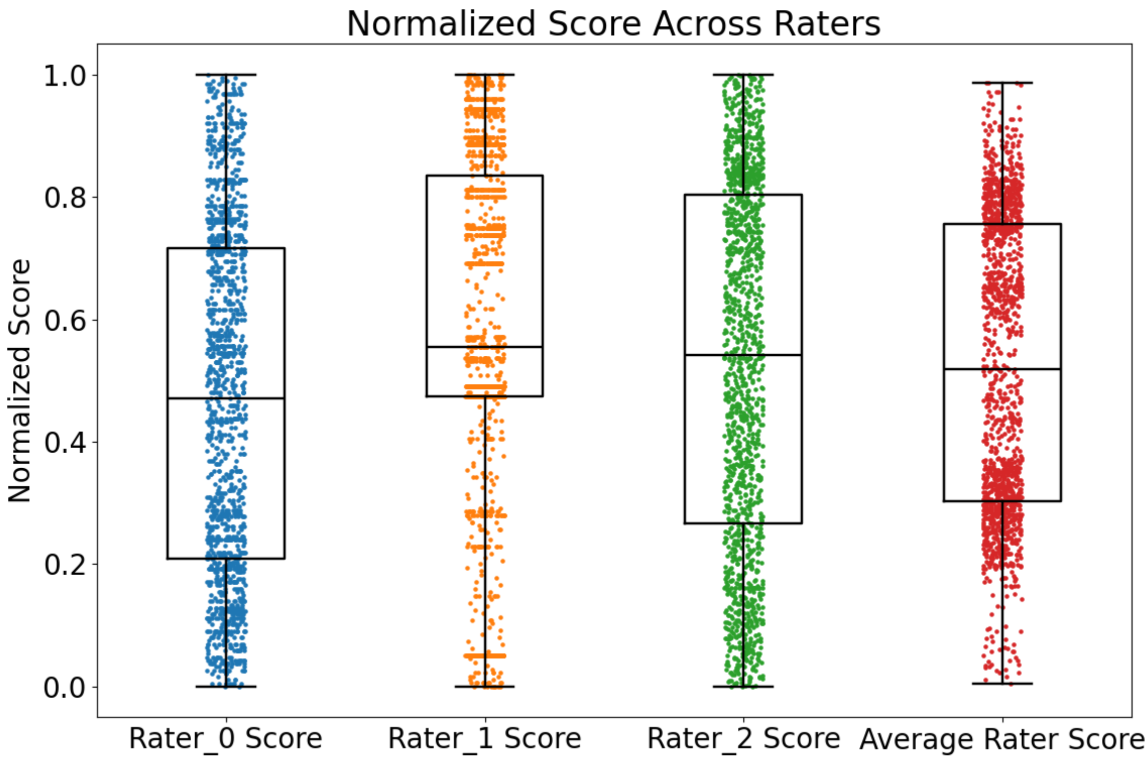


Fig. 11: Normalised rater scores, including the rater's average score. Boxes include the middle 50% of the data with the mean indicated by the horizontal line. Jitter of data along the x-axis is added only to improve visualization (to help show density) and has no statistical meaning.

Factor	**ANOVA**	**ANOVA** p	**Kruskal-Wallis**	**Kruskal-Wallis** p
Orientation	21.3	5.57×10^{-06}	21.2	5.38×10^{-06}
Pen size	2.27	0.132	3.20	0.0736
Dominance	2750	0.0	890	4.57×10^{-195}

Table 10: ANOVA and Kruskal-Wallis p-Values for data separated into subsets by a single factor. The Bonferonni correct has been applied.

Figure 12 shows the distribution of the average normalized scores of all samples, along with the kernel density estimate, a statistical estimate of the distribution of the data. From visual inspection, the data is bimodal. We further analysed each of the three factors individually. The results are shown in Figure 13 which shows the distribution as a histogram (with kernel) and as a box plot showing each sample. It is clear from this figure that the bimodality is caused by the participant's handedness – with the dominant hand showing lower scores (i.e. clearer) then the non-dominant hand. The handedness effect is carried over into the other two graphs which show smaller effects (which we quantified in Section 4.3). Surprisingly, Figure 13 shows that assessor 2 produced assessments that are clumped. Assessor 2 appears to have separated the samples by category using only the writing sample. Further investigation has not revealed any foul play in this assessors work, and it seems this assessor is simply naturally very consistent at matching clarity with category.

For each factor we performed an ANOVA then a Kruskal-Wallis test for dominance to determine whether one aspect of a factor dominates over the other. The results are shows in Table 10 which shows the size of the effect and the p-value for significance (with the Bonferroni correction). Only two factors show statistical significance at the p=0.05 level. That is, using the dominant hand results in clearer writing than the non-dominant hand, writing on a horizontal surface results in clearer writing than a vertical surface, but clarity is not affected by the use of the pen or marker grips.

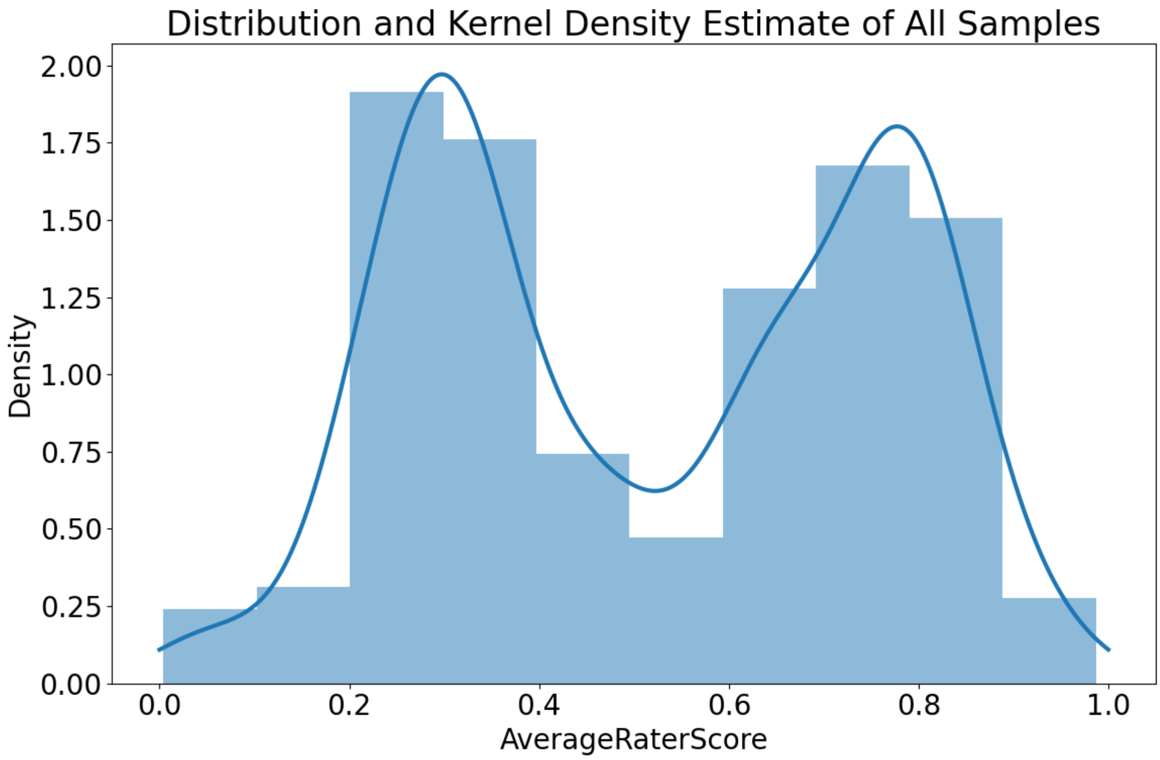
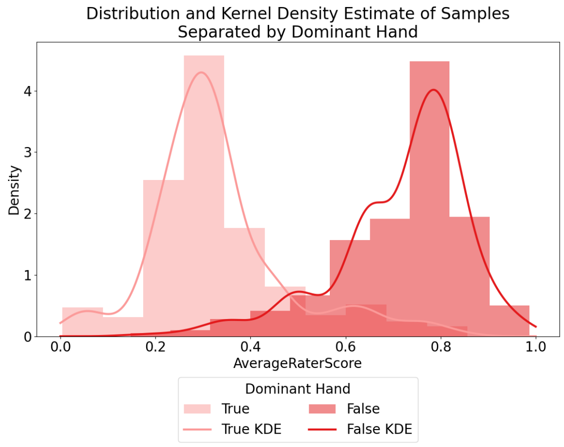


Fig. 12: Distribution and kernel density estimate of the average normalised rankings of the handwriting samples showing a bimodal distribution.

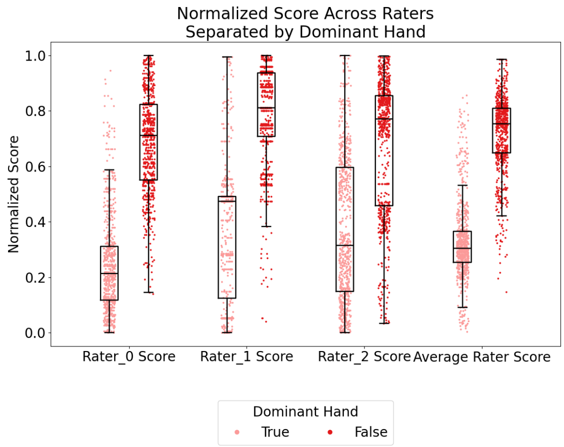
Main Factors	**Coefficient**	**p-value**
Intercept	0.746	0.0
Dominant Hand (Yes)	-0.443	0.0
Orientation (Vertical)	0.003	0.85
Pen Size (Pen)	-0.113	0.0
Two-Way Interaction Effects	**Coefficient**	**p-value**
Dominant Hand × Orientation	0.035	0.09
Dominant Hand × Pen Size	0.111	0.0
Orientation × Pen Size	0.115	0.0
Three-Way Interaction Effect	**Coefficient**	**p-value**
Dominant Hand × Orientation × Pen Size	-0.078	0.006

Table 11: The intercept and coefficients of each factor for a linear model fitted to the average rater score. The assumed value for the factors are given in parentheses.

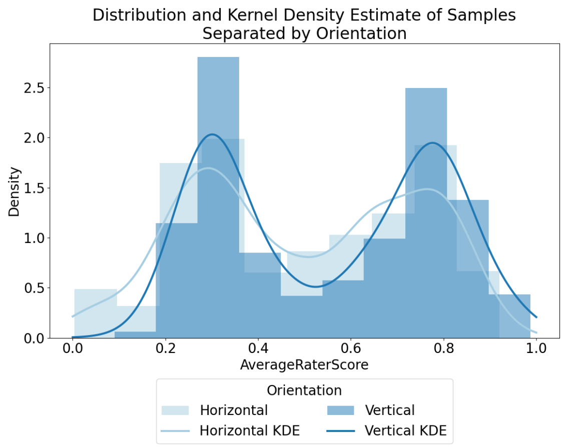
We also investigate the effect size for each factor, shown in Table 11. We fit a linear model using the least squares method, allowing us to measure the impact of each factor on the average rater score. We also present the two-way interaction effects, which are visualized in Figure 14. The three-way interaction effect had an insignificant effect. We find that hand dominance and pen size both contribute significantly at the 1% level, while orientation does not contribute significantly as a single factor. Unsurprisingly, we find the largest contribution is from the dominant hand. Pen size makes a contribution four times smaller. Orientation has a small contribution when considered alone. However, when considering the two-way effects, orientation does contribute significantly. Looking at Figure 14, we see that within each subplot, the lines are nearly parallel, meaning orientation has little effect on average rater score per the p-value in Table 11. Between subplots, the lines change gradient significantly, meaning the interaction between orientation and pen size is significant. This means the effect of changing orientation is not the same across factors. Specifically, adjusting the orientation has a much more pronounced effect when a marker is used



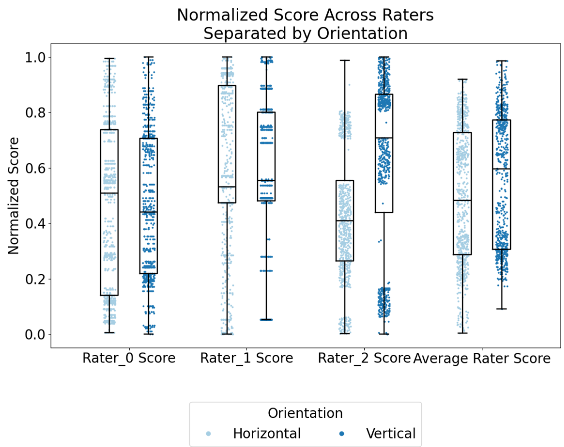
(a) Dominance of Hand.



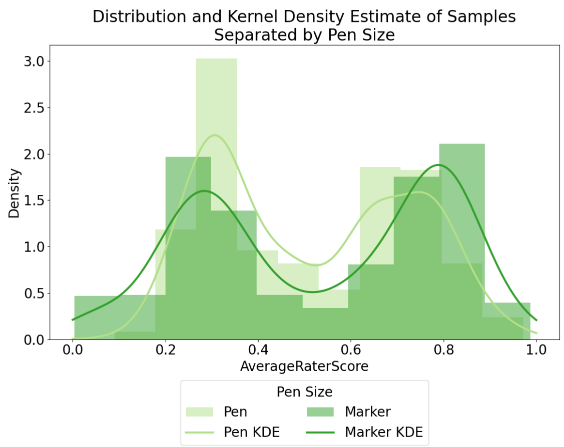
(b) Dominance of Hand.



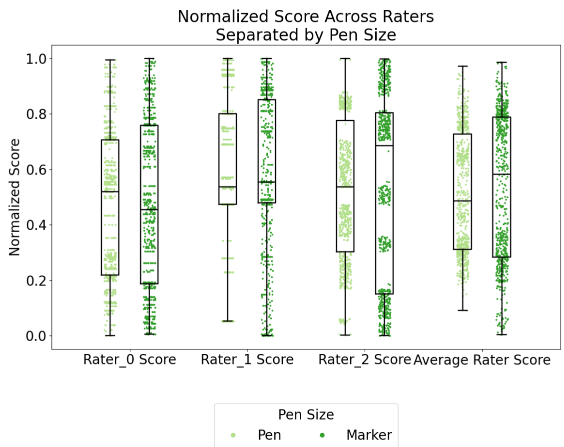
(c) Orientation of surface.



(d) Orientation of surface.



(e) Pen size.



(f) Pen size.

Fig. 13: Distribution and Kernel Density Estimate of Average Normalized Scores, split by each factor.

with the dominant hand. This matches our other results showing handedness is by far the most important factor in writing clarity, although this model cannot tell us about the outliers in our data. We may expect

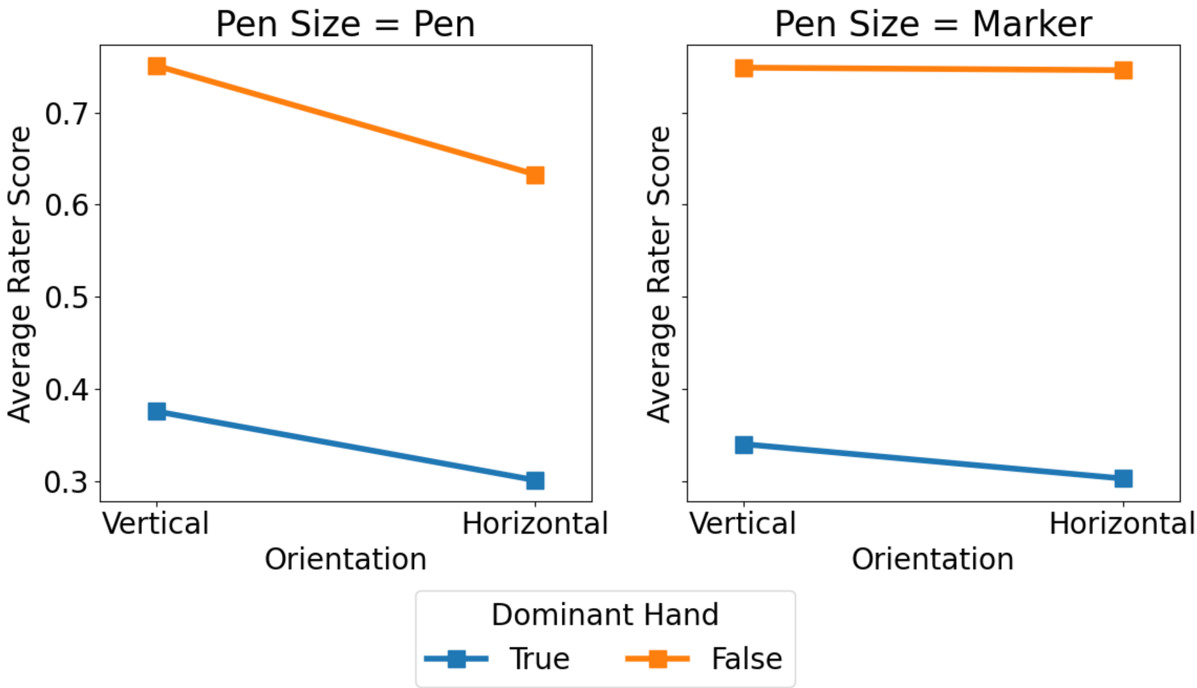


Fig. 14: Plot of the interaction effects of each factor from ANOVA.

the outliers to have significantly different relationships with these factors that are overshadowed by the majority of the measured population.

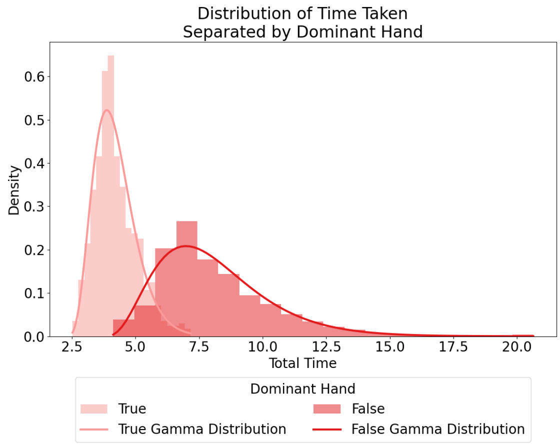
4.5 Sample Time Taken

The time taken to generate the sample of handwriting may affect its clarity. We measured the total time the pen spent in contact with the tablet (we did not measure the total writing time). We assume that each individual stroke will follow an exponential distribution — that is, no matter the condition, most writers will take a small amount of time to move the pen through the stroke, and few writers will take a long time to do so. The interpretations of what constitutes long and short times will vary between conditions, but the exponential distribution is parameterized to allow for this. Any time the pen was not in contact with the tablet, such as moving the pen into position, thinking through the motion in a sort of cognitive practice, and other preparations were also not measured, but would likely not follow an exponential distribution, as conditions the writers are unfamiliar with are likely to induce much longer planning phases.

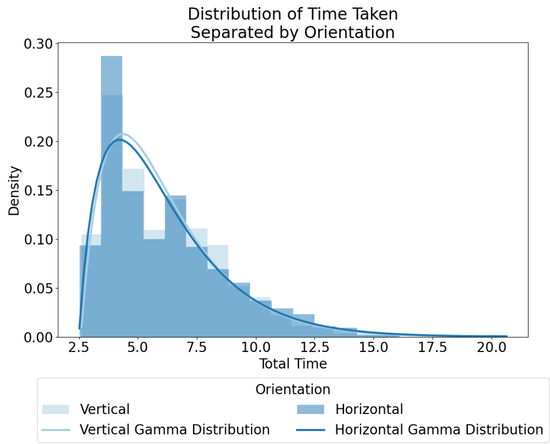
Assuming each stroke time is exponentially distributed we can conclude the total stroke time (the sum of all stroke times) must be Gamma distributed. Separating by each factor, we plot the total sample time in Figure 15. We show the Gamma distribution parameters in Table 12. The shape parameter, α, determines how skewed the distribution is, with $\alpha < 1$ peaking near 0 and $\alpha \gg 1$ resembling a normal distribution. The scale parameter, θ, determines how stretched the distribution is, with $\theta \gg 1$ indicating a distribution that is very wide. The location parameter, μ simply shifts the entire distribution left or right, moving the minimum value from 0. It is not present in Table 12, as it is simply the smallest total time taken for a condition.

Factor	α	θ
Dominant Hand	6.00	0.34
Non-Dominant Hand	3.93	1.09
Vertical	2.01	1.77
Horizontal	1.90	1.91
Pen	1.80	1.94
Marker	2.10	1.75

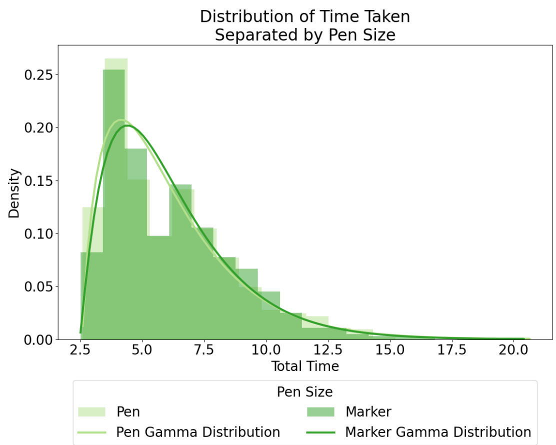
Table 12: Parameters of the Gamma distribution fit to each split based on factors.



(a) Dominance of Hand.



(b) Orientation of surface.



(c) Pen size.

Fig. 15: Histograms of Total Sample Time, split by each factor.

The clear outlier factor here is once again the split of dominant versus non-dominant hand. In all other factors the total sample time has seemingly no significant difference, which a t-test confirms. When considering dominant against non-dominant hand, however, there is a significant difference in the total sample time taken. Applying the two sample t-test to the total sample time when considering hand dominance we find a t-statistic of 43.6 with a p-value of 10^{-265}. Although the usual assumptions of the two sample t-test are violated here, namely the data is not normally distributed, the sample size is large enough and the distributions in this case are normal enough to allow it.

From this, we may infer that for the average writer from our population, writing with the non-dominant hand results in considerably longer total stroke times to produce a handwriting sample. We conjecture that this is because the average writer would not have practiced these motions ahead of time as they would have with their dominant hand. Therefore, we hypothesize that greater mental effort and hence increased thinking time is required to produce the writing (that is, they just move more slowly). It may also be the case that non-dominant handed writing induces a longer writing time due to an unfamiliar series of muscle movements, too, or a combination of these factors – we leave identification of the exact cause to future work. Non-dominant handed writing being less clear than dominant handed writing ironically suggests that the longer the participant took to write, the less clear the writing.

4.6 Categorical Analysis

In the previous sections we demonstrated that the use of the dominant hand for writing has a statistically significant effect on clarity, as does the orientation of the surface. In this section we examine each of the 8 categories individually.

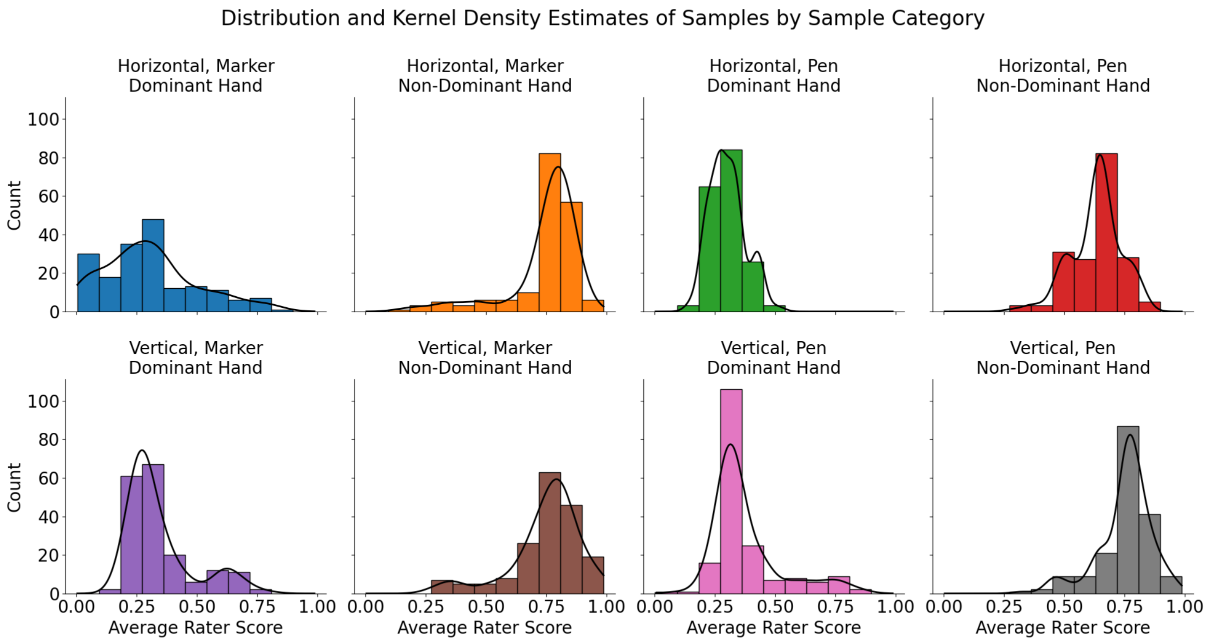


Fig. 16: Distribution and Kernel Density Estimate of average normalized score.

Category Shorthand	Mean Normalized Score	Standard Deviation	Shapiro-Wilk p-Value
HMD	0.697	0.191	5.98×10^{-06}
HMN	0.254	0.145	1.22×10^{-16}
HPD	0.699	0.0732	5.02×10^{-04}
HPN	0.367	0.102	7.41×10^{-05}
VMD	0.660	0.137	3.02×10^{-14}
VMN	0.252	0.145	2.24×10^{-10}
VPD	0.624	0.141	7.54×10^{-15}
VPN	0.249	0.110	2.37×10^{-09}

Table 13: Statistics of the samples, split into the 8 categories.

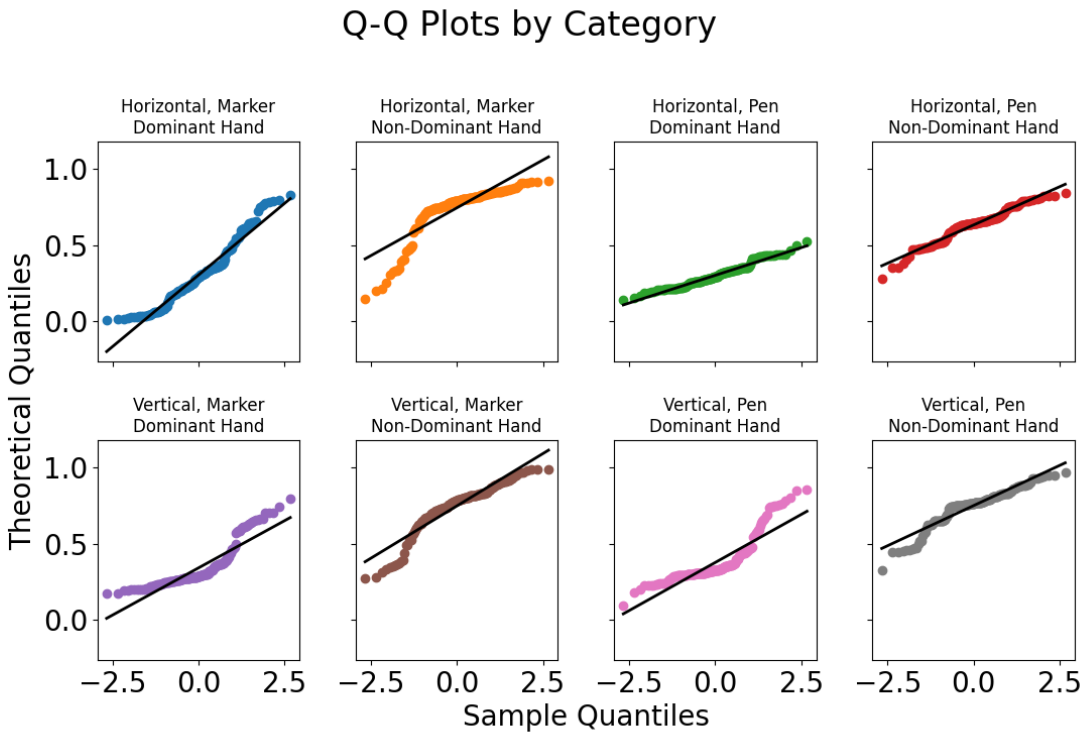


Fig. 17: Q-Q Plot of Average Normalized Score by Category.

Figure 16 shows the distribution of average normalised score for each of the 8 categories we examined. Dominant-hand writing appears to be clearer than non-dominant-handed writing, regardless of the other factors. From visual inspection, all eight distributions appear normal, as might be expected — so we tested this using the Shapiro-Wilk test. The p values in Table 13 show that, contrary to observation, none of the distributions are normal – which is counter-intuitive as many human skills are normally distributed. The Shapiro-Wilk test is prone to giving false negatives when the sample size is large (a small number of outliers can cause the test to fail). To examine this more closely, we generated the quantile–quantile (Q-Q) plots for each category (Figure 17). The Q-Q plot shows how normally distributed a dataset is without a heavy reliance on every data point conforming to the normal. The red line shows the expected distribution (scaled and shifted to match the mean and standard deviation of the data), a perfectly normally distributed dataset would fall exactly along the red line, while less normal distributions may stray from the line. It is clear that writing with the dominant hand on a horizontal surface with a pen (HPD) is close to normally distributed, as is non-dominant writing with a pen on the horizontal surface (HPN), albeit substantially less clear.

Our initial observation that some people appear able to write with their non-dominant hand on a vertical surface using a marker is represented in the VMN plot. While the middle of the data follows a normal distribution, the edges stray, suggesting that the effects on handwriting are more pronounced than expected for both the “best” and “worst” writers. This may be of interest for future research, particularly around specialized techniques or treatments that are most effective a small proportion of the population.

Figure 18 shows the average normalized score of each sample by category. Here we can see more clearly how spread some categories are compared to others, as well as the means and outliers of each category. HMD achieves the lowest scores, but has the highest inter-quartile range of all categories, perhaps suggesting some writers produce better handwriting when using an instrument with a larger grip, while other writers produce much worse writing. This shows an interesting divide in the measured population. In all categories involving the non-dominant hand, the mean score is consistently higher than the corresponding dominant category. However, we also see a large number of outliers for both dominant and non-dominant categories. For example, compare the plots for VMD and VMN: VMD has outliers stretching below the inter-quartile range, almost reaching the inter-quartile range of the VMN

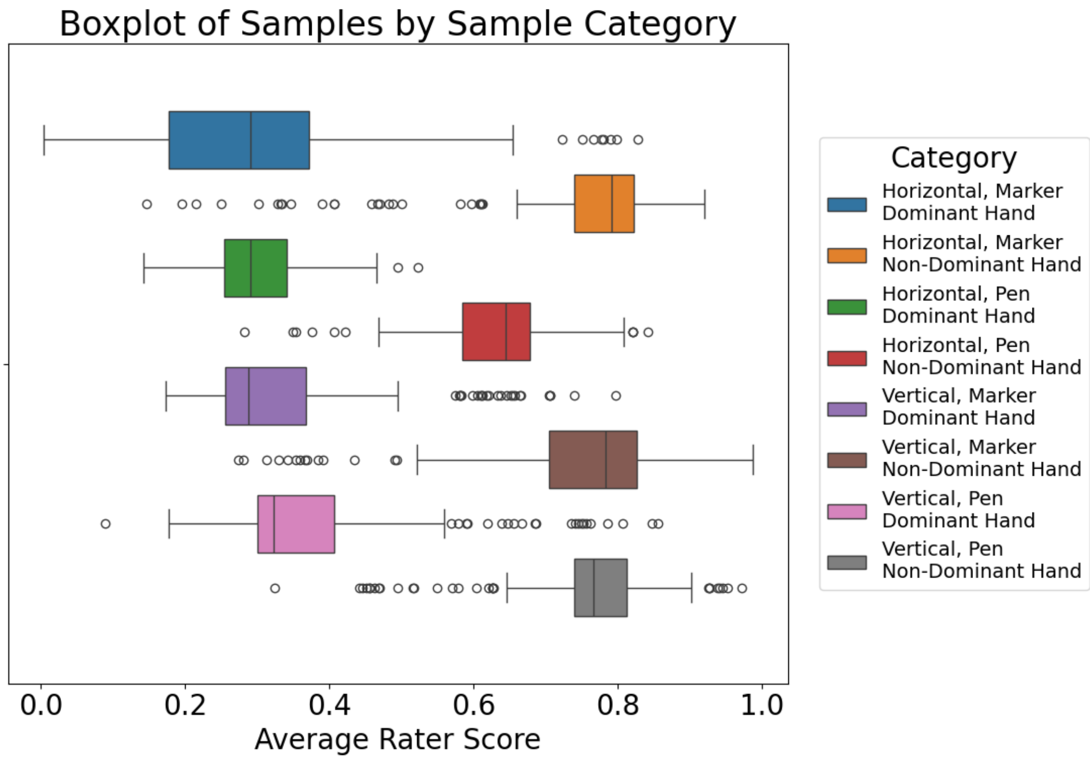


Fig. 18: Box-plots of average normalized score, smaller is clearer.

category, while VMN has the inverse with outliers stretching up towards the VMD inter-quartile range. The presence of this trend across the data, particularly across the vertical categories, may suggest that some writers are significantly impacted by the novel writing situation. Some writers may be negatively impacted, having equally "bad" writing with dominant and non-dominant hands (the outliers towards higher scores), while some writers thrive, somehow raising their non-dominant handed writing to match the clarity of their dominant handed writing at rates far exceeding the rates of ambidexterity – which is the original observation that motivated this work.

Further analysis of the 14 outliers who can write clearly with a marker, using their non-dominant hand, and on a vertical surface (VMN) is presented in Figure 19. These individuals did not self-declare as ambidextrous writers, so we assume they did not know – they are unknowingly ambidextrous writers. The figure shows that, amongst the group, the skill is normally distributed. This suggests that writing in this way is a standard behaviour for this group of individuals. An analysis of the demographics of the 14 suggests that they are representative of the population in most regards (age, sex, and education level). Different from the general population, all 14 self-reported as left-handed writers (with a ratio of 1, 4, 9 for right, ambidextrous, and left handedness). It is not clear whether these individuals had been forced to write right-handed in their past (i.e. were force-handers), or not – our data was collected anonymously and we cannot follow up. What is clear is that most (14 of 24, i.e. 58%) left-handed writers in our sample possess this skill.

5 Discussion

Our experiment was conducted on an iPad not on a white board. This made it relatively straightforward to collect the writing samples, but an iPad is a small surface and a whiteboard is a large surface. It is not clear whether the use of a smaller surface changed the writing method from gross-motor (shoulder and elbow) to fine motor (hand). Future work could look at the effect of the size of the writing surface. Our marker was an Apple Pencil encased in a whiteboard marker chassis – that is, it was nether the weight of a whiteboard marker, not did it have a tip of a whiteboard marker – and the effect of this on our experimental results is left to future work.

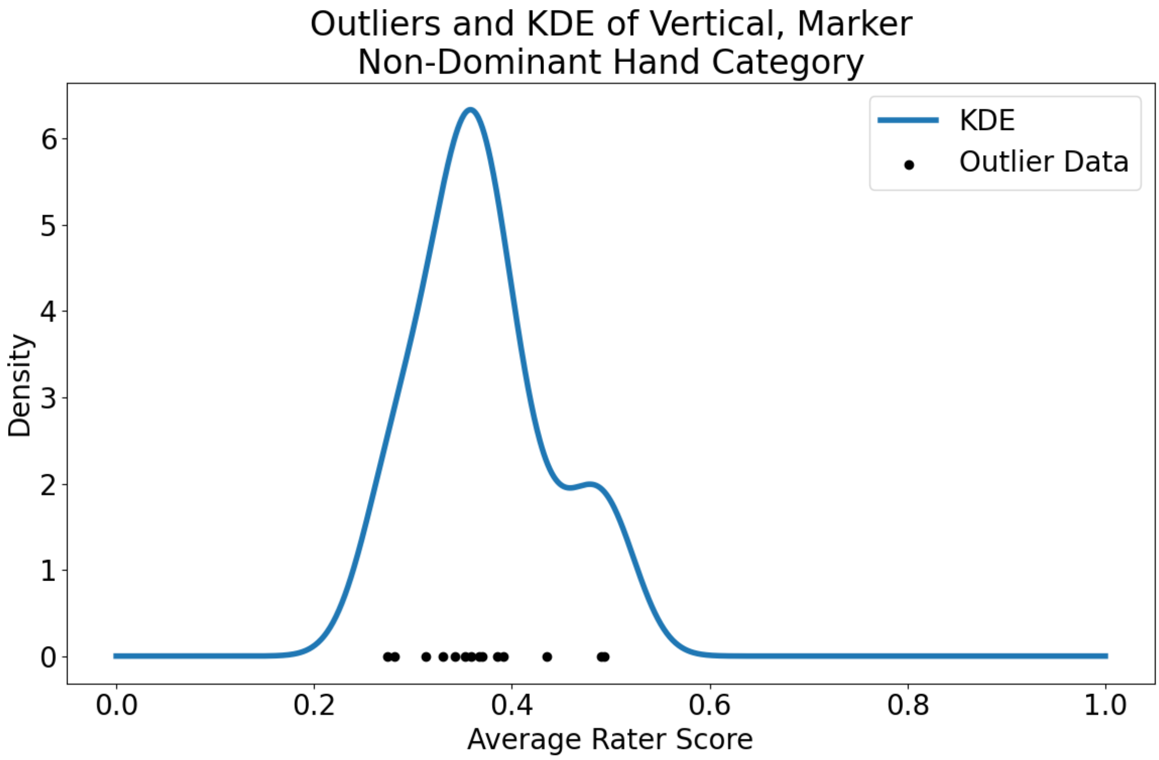


Fig. 19: The 14 outliers in the VMN category (the unknowingly ambidextrous writers) and the kernel density estimate of the average score suggests that VMN writing is normally distributed amongst this group.

Not only is an iPad dissimilar from a whiteboard, it is also dissimilar from a piece of paper; differing in surface texture, thickness, resistance, and so on. This may have affected the ability to write in the horizontal orientation, not only with the dominant hand, but with the non-dominant hand too. The effect of different surfaces on clarity is left for future work, and should include not only the smooth surface of the iPad, but also rougher surfaces such as electronic notebooks, and paper itself.

Our population, although representative of a university campus, is not representative of the general population. An older population is likely to be more familiar with writing, not only due to age, but also due a reduced exposure to modern technology (i.e. an increased exposure to pen and paper writing). Further experiments could be conducted to determine whether our result is a consequence of the age demographic of our sample.

The demographics we collected on our participants included their writing hand and their handedness. Our results show that a small proportion of the population write with their non-handedness hand. However, handedness is a spectrum rather than being clear cut, and there are ways to measure this that we did not employ. For example, the Edinburgh Handedness Inventory [26], its revisions [27], or the Fazio Laterality Inventory [28]. This investigation is focused only on writing, but there may be a link between handedness, laterality, and the ability to write with the non-dominant hand – something we leave for future work.

We identified a group who were unknowingly ambidextrous writers, all of whom were left-handed. Investigation into why this group is entirely left-handed identifies prior work with similar observation. In their experiments, Laskowski & Henneberg [29] asked 14 participants to write, with their non-dominant hand, every day for 10 days, the English alphabet and a simple sentence. They found that participants improved in writing quality. Importantly, they found that the left-handed writers had higher initial non-dominant writing scores than right handed participants. The same phenomenon that we observe. They suggest that this might be because left-handed people are forced to live in a predominantly right-handed world and are therefore more adapt at using their non-dominant hand for everyday tasks.

We assume our participants (and assessors) behaved with integrity. That is, the demographics and assessments are sound. To this end, we also assume that when the participant ranked their own writing samples, the did so “correctly” and we leave for future work any check of this – which could be performed by correlating the assessor scores against the participants scores.

No test-retest experiment was conducted, and we leave that for future work. We collected our samples anonymously in a public place, to retest the same participants would require us to approach those same participants a second time, and in doing so collect participant contact details (i.e. to potentially deanonymise some data). We did not want to do this for many reasons, including making the data available for others to use. Conducting a test-retest experiment in an environment in which the participants learn from participating is also fraught with difficulty. We observed in Section 2 that participants can learn to switch writing hand in a small number of trials. Other prior work has discussed the importance of the visual feedback loop in writing [30], and we ask the participants to look at and rank their own writing samples.

Our data could be used for other purposes. For example, it might be used to train an automated system to identify the clarity of a writing sample. With such a computerised marker, new systems that help teach writing might be developed. These might be gamified and used as a tool to teach children to write clearly. Or it might be used in the rehabilitation of RSI or stroke patients by turning an otherwise long an difficult task into a fun game.

6 Conclusions

Our work is motivated by a desire to help those who have an incapacitated dominant hand. An anecdotal observation of an individual writing clearly on a white-board with their non-dominant hand lead to this paper. To determine whether we had observed a universal trait, or a trait specific to a small segment of the population, we conducted an experiment to measure the effect on handwriting clarity of three factors: Pen grip size, surface orientation, and hand used to write. We developed hardware and software and collected 8 samples from a total of 180 members of the public found on our university campus (i.e. students). We collected a total of 1440 writing samples and thoroughly analysed the differences in writing modality that were used to generate them.

Our first research question was: *Is the ability to write clearly on a vertical surface with the non-dominant hand a universal trait?* We find that there is statistically no reason to believe that general members of the public can write on a whiteboard in the way our anecdotal user did, however we do find that there is reason to believe that there is a group who can. These unknowingly ambidextrous writers were all left-handed in our experiments.

Our second research question was: *How do the different factors affect the clarity of the writing?* We found that the hand used to write has a significant effect on the clarity of writing, as did the orientation of the writing surface. We were surprised to see that grip size did not.

We have released our data in an effort to motivate further research in this area. Some of this data has not yet been analysed – for example the orientation of the iPad when writing.

Supplementary information. Hand writing samples are available on Zenodo: https://doi.org/10.5281/zenodo.11515462.

Acknowledgements. Funding for this project was provided through University of Otago Research Grant 11954501RFH.

Declarations

- Funding: University of Otago Research Grant 11954501RFH
- Competing Interests: None
- Ethics approval and consent to participate: University of Otago, #D23/232.
- Consent for publication: Not applicable
- Data availability: Data associated with this paper is available licensed Creative Commons Attribution 4.0 International. https://doi.org/10.5281/zenodo.11515462.
- Materials availability: Not applicable
- Code availability: Some analysis code is available in our repository https://doi.org/10.5281/zenodo.11515462.

- Author contribution:
Andrew Trotman: Project design, project lead, and primary author
Matt Tyler: Data collection, and data analysis
Hayden McAlister: Statistical analysis, author
Chris Button: Project direction, and author
Lech Szymanski: Project direction

References

[1] National Handwriting Association: Why is Handwriting Important? (2023). https://nha-handwriting.org.uk/handwriting/why-is-handwriting-important/ Accessed 2023-12-04

[2] Garnett, M.F., Elgaddal, N., Rose, S.M.: Repetitive strain injuries in adults in the past 3 months: United states, 2021. National health statistics reports (189), 1–10 (2023)

[3] Raibert, M.H.: Motor control and learning by the state space model. PhD thesis, Massachusetts Institute of Technology (1977). http://hdl.handle.net/1721.1/16462

[4] Wing, A.M.: Motor control: Mechanisms of motor equivalence in handwriting. Current Biology **10**(6), 245–248 (2000) https://doi.org/10.1016/S0960-9822(00)00375-4

[5] van Galen, G.P.: Handwriting: Issues for a psychomotor theory. Human Movement Science **10**(2), 165–191 (1991) https://doi.org/10.1016/0167-9457(91)90003-G

[6] Gooderham, S.E., Bryden, P.J.: Does your dominant hand become less dominant with time? the effects of aging and task complexity on hand selection. Developmental Psychobiology **56**(3), 537–546 (2014) https://doi.org/10.1002/dev.21123

[7] Meulenbroek, R.G.J., Thomassen, A.J.W.M., Rosebaum, D.A., Loukopoulos, L.D., Vaughan, J.: Adaptation of a reaching model to handwriting: How different effectors can produce the same written output, and other results. Psychological Research **59**, 64–74 (1996)

[8] Jacqueline Fagard, A.C., Bonnet, P.: How should "ambidexterity" be estimated? Laterality **20**(5), 543–570 (2015) https://doi.org/10.1080/1357650X.2015.1009089

[9] Graham, S.: A review of handwriting scales and factors that contribute to variability in handwriting scores. Journal of School Psychology **24**(1), 63–71 (1986) https://doi.org/10.1016/0022-4405(86)90043-9

[10] Gargot, T., Thibault, A., Pellerin, H., Zammouri, I., Anzalone, S.M., Casteran, L., Johal, W., Dillenbourg, P., Cohen, D., Jolly, C.: Acquisition of handwriting in children with and without dysgraphia: A computational approach. PLoS ONE **15**(9), 0237575 (2020) https://doi.org/10.1371/journal.pone.0237575

[11] Ikermane, M., El Mouatasim, A.: Digital handwriting characteristics for dysgraphia detection using artificial neural network. Bulletin of Electrical Engineering and Informatics **12**(3), 1693–1699 (2023) https://doi.org/10.11591/eei.v12i3.4571 . Corresponding Author: Mohamed Ikermane, Laboratory LABSI, Faculty of Sciences, Ibn Zohr University, Agadir, Morocco, Email: ikermane.mohamed@gmail.com

[12] Seifikar, M., Minh, L.N.P., Arabzadeh, N., Clarke, C.L.A., Smucker, M.D.: A preference judgment tool for authoritative assessment. In: Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval. SIGIR '23, p. 5. ACM, New York, NY, USA (2023). https://doi.org/10.1145/3539618.3591801

[13] Yancosek, K.E., Gulick, K.: Handwriting for Heroes: Learn to Write with Your Non-Dominant Hand in Six Weeks. Loving Healing Press, Incorporated, Ann Arbor, MI (2009). https://books.google.co.nz/books?id=OTx1b1GsYnwC

[14] Yancosek, K.E., Calderhead, W.J.: Efficacy of *Handwriting for Heroes*, a novel hand dominance transfer intervention. Hand Therapy **17**(1), 15–24 (2012) https://doi.org/10.1258/ht.2011.011024

[15] Hanna Sandve, H.L., Pedersen, A.V.: Is it possible to change handedness after only a short period of practice? effects of 15 days of intensive practice on left-hand writing in strong right-handers. Laterality **24**(4), 432–449 (2019) https://doi.org/10.1080/1357650X.2018.1534856 . PMID: 30319073

[16] Walker, L., Henneberg, M.: Writing with the non-dominant hand: Cross-handedness trainability in adult individuals. Laterality **12**(2), 121–130 (2007) https://doi.org/10.1080/13576500600989665 . PMID: 17365628

[17] Mutai, H., Sato, M., Kitahara, T., Hamada, A., Ozawa, K., Noji, A., Sugimoto, S., Iwanami, J., Sagari, A.: Effects of occupational therapy on improvements in the handwriting ability of the adult non-dominant hand: An exploratory randomised controlled trial. Australian Occupational Therapy Journal **69**(1), 15–24 (2022) https://doi.org/10.1111/1440-1630.12764

[18] Marcori, A.J., Monteiro, P.H.M., Okazaki, V.H.A.: Changing handedness: What can we learn from preference shift studies? Neuroscience & Biobehavioral Reviews **107**, 313–319 (2019) https://doi.org/10.1016/j.neubiorev.2019.09.019

[19] Shrout, P.E., Fleiss, J.L.: Intraclass correlations: Uses in assessing rater reliability. Psychological Bulletin **86**(2), 420–428 (1979) https://doi.org/10.1037/0033-2909.86.2.420

[20] University of Otago: Quick statistics (2023). https://www.otago.ac.nz/about/quickstats Accessed 2023-12-05

[21] Kovel, C.G.F., Carrión-Castillo, A., Francks, C.: A large-scale population study of early life factors influencing left-handedness. Scientific Reports **9**(1), 584 (2019) https://doi.org/10.1038/s41598-018-37423-8

[22] Vuoksimaa, E., Koskenvuo, M., Rose, R.J., Kaprio, J.: Origins of handedness: A nationwide study of 30161 adults. Neuropsychologia **47**(5), 1294–1301 (2009) https://doi.org/10.1016/j.neuropsychologia.2009.01.007

[23] Cicchetti, D.V.: Guidelines, criteria, and rules of thumb for evaluating normed and standardized assessment instruments in psychology. Psychological assessment **6**(4), 284–290 (1994)

[24] American Physical Therapy Association: Physical Therapy Guide to Carpal Tunnel Syndrome (2024). https://www.choosept.com/guide/physical-therapy-guide-carpal-tunnel-syndrome Accessed 2024-01-23

[25] Wu, F.-G., Luo, S.: Performance study on touch-pens size in three screen tasks. Applied Ergonomics **37**(2), 149–158 (2006) https://doi.org/10.1016/j.apergo.2005.05.011

[26] Oldfield, R.C.: The assessment and analysis of handedness: The edinburgh inventory. Neuropsychologia **9**(1), 97–113 (1971) https://doi.org/10.1016/0028-3932(71)90067-4

[27] Williams, S.: A Major Revision of the Edinburgh Handedness Inventory: The EHI-8. https://doi.org/10.13140/RG.2.2.15176.55042/1

[28] Rachel Fazio, S.G. Kathryn J. Dunham, Denney, R.L.: An improved measure of handedness: The fazio laterality inventory. Applied Neuropsychology: Adult **20**(3), 197–202 (2013) https://doi.org/10.1080/09084282.2012.684115 . PMID: 23406292

[29] Laskowski, K., Henneberg, M.: Writing with non-dominant hand: left-handers perform better with the right hand than right handers with the left. Anthropological Review **75**(2), 129–136 (2012) https://doi.org/10.2478/v10044-012-0012-4

[30] Danna, J., Velay, J.-L.: Basic and supplementary sensory feedback in handwriting. Frontiers in

Psychology **Volume 6 - 2015** (2015) https://doi.org/10.3389/fpsyg.2015.00169