# Handwriting features measured by computer vision and their relationship with personality

*An exploratory concurrent validity study with the MBTI and the NEO-PI-R in Chilean adults (2017–2018)*

Rodrigo Farías Veloso · Cristopher Suárez · Diego Díaz Espinosa

Instituto de Ciencias del Grafismo Grafos, Santiago, Chile · contactografos.cl

**ABSTRACT**

The main criticism of graphology has been the subjectivity of its method: its results depend on the eye of the analyst. This study removed the graphologist from the measurement stage. Spontaneous handwriting samples from Chilean adults were analysed with computer-vision software developed by the authors (2017 version) that automatically extracted 43 to 47 handwriting descriptors (ink density, margins, line direction and slant, ovals, upper and lower loops, among others). The same participants completed the MBTI (n = 64–65), the NEO-PI-R (n = 51–52) and two scales of the PMA. Spearman (two-tailed) and Pearson correlations were computed. The number of significant associations clearly exceeded chance expectations (127 observed vs. 88 expected at $p < .05$; Spearman). The hypothesis stated before data collection, that greater ink density accompanies Extraversion, was supported ($\rho = .423$, $p < .001$). Associations consistent with classical theory were also observed between wide top and right margins and Introversion, rightward slant and Openness, and line regularity and Competence. Effect sizes are moderate and the design is exploratory, so these findings do not support decisions about individuals. They do show, however, that some graphological hypotheses, operationalised as automatic measures, are testable and receive empirical support, which justifies their systematic study and replication.

**Keywords:** graphology, computer vision, concurrent validity, MBTI, NEO-PI-R, extraversion, handwriting.

## 1. INTRODUCTION

Handwriting is a learned skill. With practice it becomes automatic, until it turns into a gesture that requires no attention; at the same time, each person departs from the copybook model they were taught in a personal and stable way. Graphology holds that these personal deviations preserve a trace of the writer's non-verbal language and allow hypotheses about personality to be formulated. This idea, present since Baldi (1622) and systematised by Michon, Crépieux-Jamin (1888), Klages (1917) and Pulver (1931), also draws on the experimental tradition that studied personality through motor behaviour (Allport & Vernon, 1933; Mira y López, 1940).

The accumulated evidence on classical graphology, however, has been discouraging. Meta-analyses found low or null predictive validity once text content is controlled (Neter & Ben-Shakhar, 1989; Dean, 1992), and graphological judgements have been shown to be vulnerable to illusory correlations (King & Koehler, 2000). Ben-Shakhar et al. (1986) raised a fundamental methodological objection: graphology cannot be evaluated independently of the graphologists who practise it. When a study tests graphology, it actually tests a particular analyst, with his or her training, biases and perception.

That objection has a possible answer: measuring without an analyst. The individuality of handwriting had already been demonstrated computationally, with a system that distinguished the writers of samples from 1,500 people using automatically extracted features (Srihari et al., 2002). Several groups have since attempted to extract graphological features through image processing, from neural networks for predicting behaviour (Champa & AnandaKumar, 2010)

to machine-learning systems (Hashemi et al., 2015; Joshi et al., 2015), and handwriting as a biometric signal has been extended to health (Faundez-Zanuy et al., 2020). In the line closest to this work, Chernov and Nauer (2016) proposed a computer-aided graphology to formalise the recording of signs, and Chernov and Caspers (2020) reported agreement between a formalised system and the 16PF in 58 people. Studies with manual graphological analysis have also reported associations between handwriting features and extraversion measured with inventories. Cernuda-Aspe and Pérez-Fernández (2016), using Xandró's method applied by a rater to 50 Spanish university students, found a correlation of .748 with the NEO PI-R Extraversion scale; Karami (2017) reported relationships with the Eysenck test. These studies point in the same direction as the present one, but their measurement depended on a graphologist's judgement.

What was missing in most of these works was a specific combination: classical descriptors measured fully automatically, without any graphologist, compared against validated personality inventories in the same sample. That is the purpose of this study, designed in 2017 for a Chilean population following the recommendation that psychological tests have local validity studies.

### 1.1 Hypotheses

General hypothesis: there is a significant relationship between automatically measured handwriting descriptors and scales of validated personality inventories. Specific hypothesis, recorded in the protocol before data collection: ink density (the percentage of black pixels over the whole page, the automatic equivalent of graphology's "predominance of black") is positively associated with Extraversion. All other pairings were explored without prior hypotheses, to allow relationships not described by the theory to emerge.

## 2. METHOD

### 2.1 Design

Correlational, descriptive and exploratory concurrent validity study. Each descriptor was correlated with every scale of the instruments.

### 2.2 Participants

Chilean adults who had completed secondary education, recruited by snowball sampling and through universities and job-placement institutions. The design called for 400 participants; the analysis reported here includes 64–65 people with a handwriting sample and the MBTI, of whom 51–52 also completed the NEO-PI-R and 34–36 the PMA scales. The project's MBTI database included 233 people, but only those who provided handwriting are analysed here. Participants were not in a selection process and therefore had no incentive to present themselves favourably. They received an individual report of their results.

### 2.3 Instruments

**Handwriting sample.** Each person drew a person in the rain on a standardised form and then wrote, on two unlined letter-size sheets, an invented story about that drawing, at least one and a half pages long, in ballpoint pen and in their usual handwriting. The drawing was used only as a stimulus to elicit spontaneous writing. To avoid altering the top margin, the title of the story was written on a separate line. The sheets were digitised with a scanner.

**Automated handwriting analysis.** The software, developed by the authors in its 2017 version (then called InkSight, now GrafoMetrics) and programmed in Python with computer-vision techniques, binarises the image and computes descriptors without human intervention: ink density; mean, irregularity and slope of the margins; top and bottom margins; line direction and irregularity; slant of the axes and its variability; number of lines, words and strokes; cohesion; and measures of ovals and upper and lower loops.

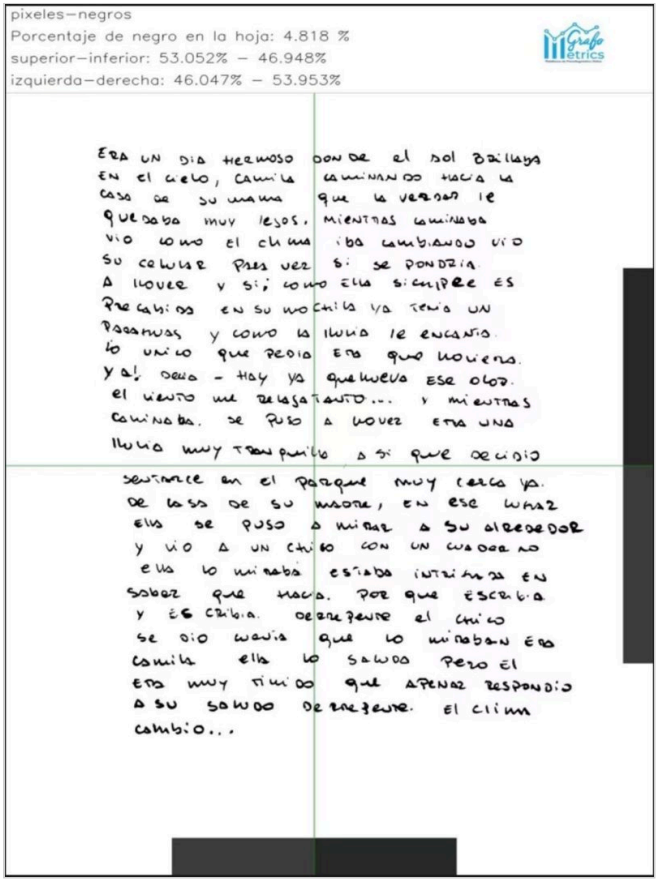



**Figure 1.** Ink density. A sample binarised by the software: 4.818% of the pixels on the page are ink. The lines divide the page into quadrants.

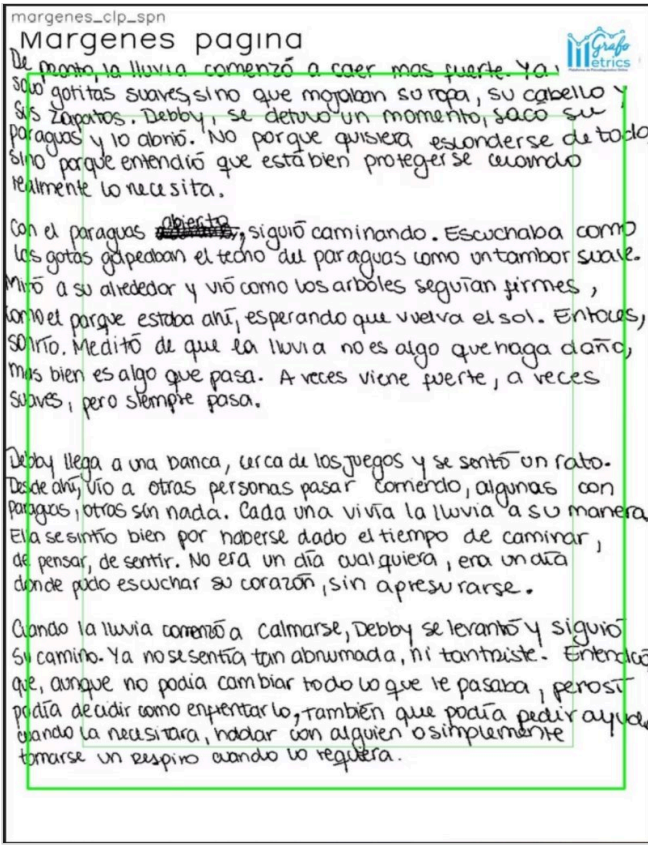



**Figure 2.** Margins. The software measures the distance between the text and each edge of the page. The green rectangles mark the expected range according to the norm; here the text overflows it on the left and on the right.

The figures illustrate the measurement principle with the current version of the software (GrafoMetrics). The study used the 2017 version, which applied the same principles. Samples are anonymised; names within the texts are characters in the stories.

**MBTI** (Myers et al., 1998): psychological type inventory of 96 forced-choice items with four dichotomous dimensions (E–I, S–N, T–F, J–P). E, S, T and J were coded 1; I, N, F and P, 0. Type was also checked in a personal interview. **NEO-PI-R** (Costa & McCrae, 1992): 240 items; five factors and thirty facets (Spanish adaptation, in which the factor and facet labels follow the Spanish edition). **PMA** (Thurstone, 1938): Reasoning and Verbal fluency scales.

In this sample, the four MBTI dimensions were related to the NEO-PI-R factors that measure similar constructs, with magnitudes close to those of the manual's normative sample (Table 1). This indicates that both instruments behaved as expected in a Chilean population.

**Table 1. Correspondence between the MBTI and the NEO-PI-R: normative sample and project sample**

| MBTI dimension | NEO-PI-R factor | McCrae & Costa (1989), men / women | This project (n = 203) | Same direction |
|---|---|---|---|---|
| Extraversion–Introversion | Extraversion | .74 / .69 | .484 | Yes |
| Sensing–Intuition | Openness | .72 / .69 | .413 | Yes |
| Thinking–Feeling | Agreeableness | .44 / .46 | .470 | Yes |
| Judging–Perceiving | Conscientiousness | .49 / .46 | .426 | Yes |

Absolute values; the sign depends on which pole is coded high. McCrae and Costa (1989): N = 468 (267 men, 201 women), all $p < .001$. This project: Spearman correlation, all $p < .001$. Neuroticism has no MBTI counterpart.

### 2.4 Analysis

Two analyses of the same database are reported. The main analysis, from February 2018, uses Spearman correlations with two-tailed significance, which are more conservative and robust to extreme cases. The 2017 analysis uses Pearson correlations (point-biserial for the MBTI) with one-tailed significance. Associations that were significant in both analyses and had the same sign are considered more robust. To estimate whether the set of results exceeded chance, the number of significant pairings was compared with the number expected under the null hypothesis using a binomial test. The original analyses were run in SPSS; counts, intervals and comparisons were recomputed in 2026 from the result tables.

## 3. RESULTS

**Table 2. Sample and instruments**

| Component | Detail | n |
|---|---|---|
| Handwriting + MBTI | Chilean adults, no selection incentive | 64–65 |
| Handwriting + NEO-PI-R | Subgroup with the complete inventory | 51–52 |
| Handwriting + PMA | Reasoning and Verbal fluency | 34–36 |
| Automatic descriptors | Computer-vision software (2017 version) | 43–47 |
| Psychological scales | 4 MBTI, 5 NEO factors and 30 facets, 2 PMA | 41 |

### 3.1 The overall results against chance

If handwriting descriptors bore no relation to personality, with a .05 threshold about 5% of the pairings would be expected to be significant by chance alone. In both analyses the observed number was clearly higher (Table 3).

**Table 3. Significant correlations observed versus expected by chance**

| Analysis | Threshold | Pairings | Expected by chance | Observed | p (binomial) |
|---|---|---|---|---|---|
| Spearman, two-tailed (Feb. 2018) | p < .05 | 1,763 | 88.2 | 127 | < .001 |
| Spearman, two-tailed (Feb. 2018) | p < .01 | 1,763 | 17.6 | 27 | .022 |
| Spearman, two-tailed (Feb. 2018) | p < .001 | 1,763 | 1.8 | 4 | — |
| Pearson, one-tailed (2017) | p < .05 | 1,927 | 96.4 | 234 | < .001 |
| Pearson, one-tailed (2017) | p < .01 | 1,927 | 19.3 | 51 | < .001 |

The binomial test assumes independent pairings. Because many scales are correlated with one another (for example, the facets of a single NEO-PI-R factor), these probabilities should be read as an optimistic approximation; the excess of results, however, appears in both analyses.

One hundred pairings were significant in both analyses with the same sign (Appendix, Table A1).

### 3.2 The a priori hypothesis: ink density and Extraversion

Ink density was associated with the Extraversion pole of the MBTI ($\rho = .423$, $p < .001$, $n = 64$): extraverted people cover a larger proportion of the page with ink. It was the second strongest association in the whole main analysis and the strongest among those involving the MBTI. Ink density was not associated, however, with the NEO-PI-R Extraversion factor ($\rho = .06$), a point discussed below.

### 3.3 Other associations consistent with theory

Table 4 brings together the associations that were significant in both analyses and that match classical interpretations. Wide margins (top and right), which the graphological tradition reads as distance, reserve and prudence (Vels, 1997), accompanied the Introversion pole. A wide right margin was also associated with Dutifulness, Order and the Conscientiousness factor. Rightward slant, interpreted as movement towards others and towards the new, was associ-

ated with Openness to experience. Irregularity in line direction, which the tradition links to instability, was associated with lower perceived Competence. The number of lines written, a measure of productivity, accompanied Extraversion and showed the strongest association in the study with the Values facet, a finding not anticipated by the theory.

**Table 4. Main associations, consistent with graphological theory or with the a priori hypothesis**

| Handwriting descriptor | Scale | ρ | p (2-t) | 95% CI | n | r (2017) |
|---|---|---|---|---|---|---|
| Percentage of black pixels **(a priori hypothesis)** | MBTI Extraversion | .423 | < .001 | .18 to .62 | 64 | .390 |
| Wider top margin | MBTI Extraversion | −.406 | < .001 | −.60 to −.16 | 64 | −.357 |
| Wider right margin | MBTI Extraversion | −.305 | .014 | −.52 to −.05 | 64 | −.259 |
| Number of lines written | MBTI Extraversion | .287 | .021 | .03 to .51 | 64 | .313 |
| Rightward slant | NEO Openness | .323 | .019 | .04 to .56 | 52 | .301 |
| Line direction irregularity | NEO C1 Competence | −.310 | .025 | −.55 to −.02 | 52 | −.389 |
| Wider right margin | NEO C3 Dutifulness | .366 | .008 | .09 to .59 | 52 | .242 |
| Wider right margin | NEO C2 Order | .361 | .009 | .08 to .59 | 52 | .364 |
| Wider right margin | NEO Conscientiousness (factor) | .317 | .022 | .03 to .55 | 52 | .279 |
| Number of lines written *(emergent)* | NEO O6 Values | .543 | < .001 | .30 to .72 | 52 | .526 |
| Percentage of black pixels *(emergent)* | NEO O6 Values | .346 | .012 | .06 to .58 | 52 | .416 |

ρ: Spearman correlation, February 2018 analysis, two-tailed significance. 95% CI: approximate interval using Fisher's z transformation with the Bonett and Wright (2000) adjustment. r: Pearson correlation from the 2017 analysis (one-tailed significance, all p < .05). For the MBTI, positive values indicate the Extraversion pole (E = 1; I = 0).

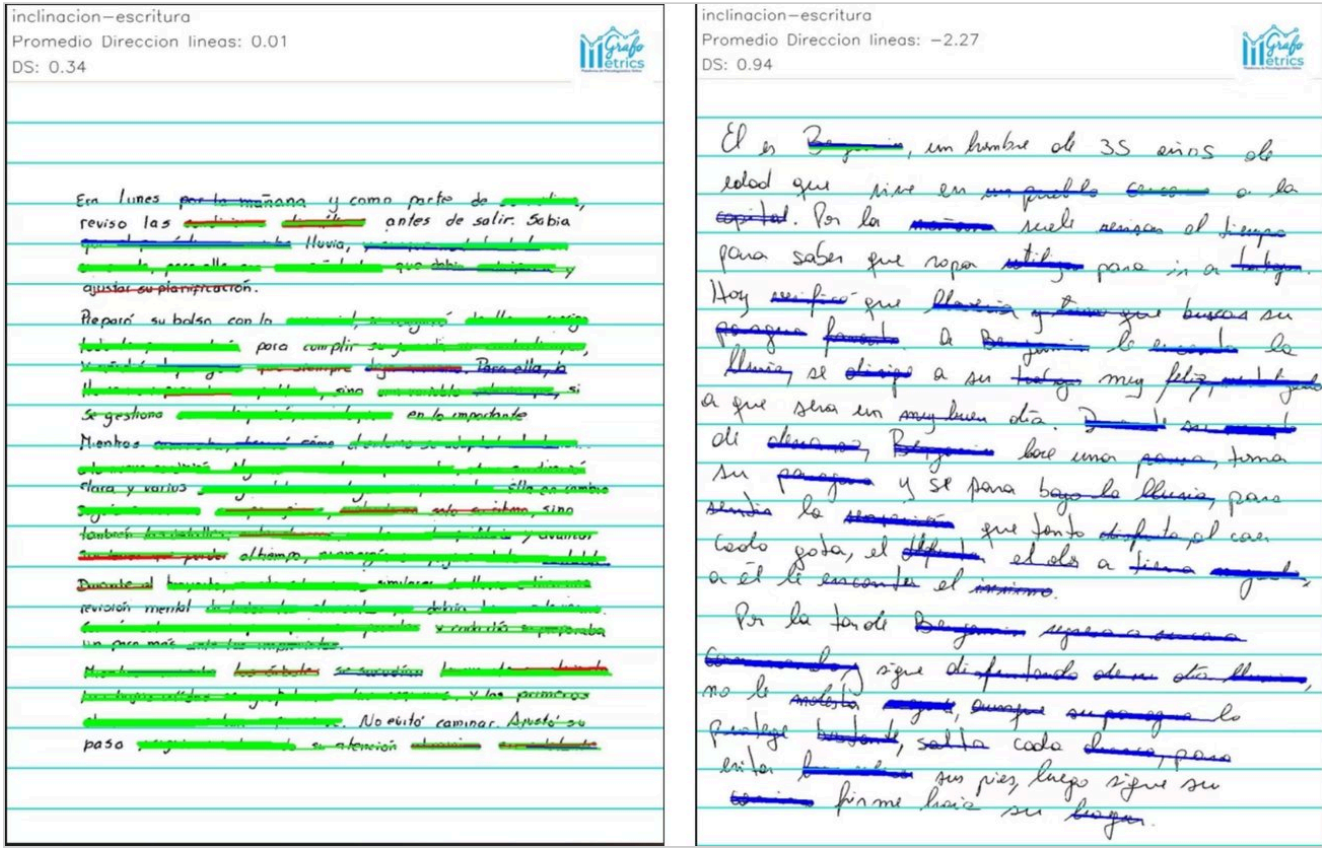



**Figure 3.** Line direction and regularity. Left: mean slope of 0.01° and standard deviation of 0.34; the lines run almost along the reference. Right: descending lines, with a mean slope of −2.27° and a standard deviation of 0.94. In the study, greater line irregularity was associated with lower Competence (NEO C1).

### 3.4 Stability of the main association

The association between ink density and Extraversion was first observed in a pilot group of 16 people, with a very high coefficient. With the full sample the coefficient decreased, as expected when an initial result comes from few cases, but it remained significant at every stage (Table 5).

**Table 5. The association between ink density and Extraversion (MBTI) by sample size**

| Stage | Date | People | Coefficient | Significance |
|---|---|---|---|---|
| Pilot | 2017 | 16 | r = .723 | p < .001 (one-tailed) |
| Full sample | 2017 | 65 | r = .390 | p < .001 (one-tailed) |
| Full sample, non-parametric analysis | Feb. 2018 | 64 | ρ = .423 | p < .001 (two-tailed) |
| Extension with an uncleaned database (see Limitations) | Mar. 2018 | ≈ 110–120 | .209 | p < .05 (two-tailed) |

The decrease of the coefficient as the sample grows is the expected pattern when a first result comes from few cases. What matters is that the association kept its direction and stayed above the significance threshold at every stage.

## 4. DISCUSSION

This study tested graphological hypotheses under a condition that the critique by Ben-Shakhar et al. (1986) considered indispensable: measurement did not depend on any graphologist. Descriptors were computed by a program, reproducibly, and compared against validated inventories completed by people with no incentive to present themselves favourably. Under these conditions, the number of significant associations exceeded what chance would produce, and the hypothesis recorded in the protocol before data collection was supported.

Several associations match interpretations that graphology formulated more than a century ago from observation: the spread of ink over the page accompanies outward orientation; distance from the edges, reserve; rightward slant, openness; line regularity, a sense of competence. These results do not prove graphology as a complete interpretive system. They suggest something narrower and, at the same time, more useful for research: that at least part of its hypotheses can be translated into objective measures and tested empirically, as is done with any other psychological instrument under development.

The dissociation between MBTI and NEO-PI-R Extraversion deserves attention. The MBTI E–I dimension describes where psychic energy is directed, in the Jungian tradition, whereas the NEO Extraversion factor brings together facets of sociability, activity and positive emotions. The two measures are related but not identical: in the MBTI normative sample (N = 468), McCrae and Costa (1989) reported correlations of −.74 and −.69 between the E–I scale and NEO Extraversion, and in this project's database the correlation was .484 (Table 1). They therefore share between a quarter and a half of their variance. Ink density may relate to the part specific to the Jungian dimension rather than to the sociability measured by the NEO; the result may also reflect differences between the MBTI group and the smaller subgroup that completed the NEO. This question should be addressed in a replication.

Effect sizes, between .29 and .54 in absolute value, are moderate. They are comparable to those usually reported for expressive and projective methods, in which the observed behaviour is not a deliberate self-report. But they do not allow anyone's personality to be inferred from their handwriting: they describe tendencies in groups.

### 4.1 Limitations

First, sample size: the design aimed at 400 people and the analysis reached 64–65, which produces wide confidence intervals. Second, the exploratory nature of the study: with 1,763 pairings and no correction for multiple comparisons, some of the individual associations in the Appendix may be due to chance; with a strict correction for the whole set (Benjamini & Hochberg, 1995) only a few remain. For this reason the a priori hypothesis, the overall excess of results and the convergence between two analyses are given priority here. Third, the result tables were recov-

ered from project files; the individual-level database was not available for this report, so sex, age and writing instrument could not be controlled. Fourth, a later analysis with an extended sample (March 2018, around 110–120 people) showed correlations above .9 between descriptors of different kinds, consistent with a scale inconsistency in the extraction, and is not used. In that analysis, the association between ink density and Extraversion remained significant, although smaller (Table 5). Fifth, the descriptors correspond to an early version of the software, several of which were later revised.

### 4.2 Future research

We propose: (a) a replication with at least 300 people, with hypotheses registered before data collection; (b) making anonymised individual-level data available for reanalysis; (c) controlling for sex, age, handedness and writing instrument; (d) including criteria other than self-report, such as job performance or clinical assessment; and (e) comparing rule-based approaches with machine-learning models trained on examples.

## 5. CONCLUSION

In a sample of Chilean adults, handwriting descriptors computed automatically by computer vision, without the intervention of graphologists, were associated with scales of validated personality inventories in a proportion that exceeds chance. The a priori hypothesis of a relationship between ink density and Extraversion was supported, and several additional associations match classical graphological theory. These results do not validate graphology as a system. They do indicate that some of its hypotheses are testable and find empirical support, and that the combination of automatic measurement and statistics offers a path to study them with the rigour that science demands. We invite other researchers to replicate and extend them.

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## APPENDIX. ASSOCIATIONS CONVERGING IN BOTH ANALYSES

**Table A1. The 40 strongest associations that were significant and had the same sign in both analyses (out of 100)**

| Descriptor | Scale | ρ | p 2-t | n | r | p 1-t |
|---|---|---|---|---|---|---|
| Number of lines written | NEO O6 Values | 0.543 | < .001 | 52 | 0.526 | < .001 |
| Percentage of black pixels (ink density) | MBTI: Extraversion (vs. Introversion) | 0.423 | < .001 | 64 | 0.390 | < .001 |
| Number of words | NEO O6 Values | 0.462 | < .001 | 52 | 0.413 | .001 |
| Top margin | MBTI: Extraversion (vs. Introversion) | -0.406 | < .001 | 64 | -0.357 | .002 |
| Number of words | NEO O1 Fantasy | 0.433 | .001 | 52 | 0.414 | .001 |
| Cohesion (strokes per word) | NEO O1 Fantasy | -0.419 | .002 | 52 | -0.290 | .019 |
| Number of ovals | NEO O1 Fantasy | 0.410 | .003 | 52 | 0.366 | .004 |
| Lower loop height/width | NEO O4 Actions | -0.426 | .003 | 46 | -0.457 | < .001 |
| Right margin slope | NEO A5 Modesty | 0.389 | .004 | 52 | 0.259 | .033 |
| Number of ovals | NEO: Openness | 0.381 | .005 | 52 | 0.346 | .006 |
| Bottom margin | NEO C1 Competence | -0.377 | .006 | 52 | -0.363 | .004 |
| Slant variability | NEO N4 Self-consciousness | -0.373 | .006 | 52 | -0.332 | .009 |
| Slant variability | NEO N6 Vulnerability | -0.370 | .007 | 52 | -0.306 | .014 |
| Upper loop height | NEO O6 Values | -0.397 | .007 | 45 | -0.316 | .018 |
| Cohesion (strokes per word) | NEO C6 Deliberation | 0.368 | .007 | 52 | 0.379 | .003 |
| Number of ovals | NEO O2 Aesthetics | 0.366 | .008 | 52 | 0.307 | .014 |
| Right margin (mean) | NEO C3 Dutifulness | 0.366 | .008 | 52 | 0.242 | .044 |
| Number of upper loops | NEO E5 Excitement-seeking | -0.391 | .008 | 45 | -0.468 | < .001 |
| Upper loop/middle zone ratio | NEO O6 Values | -0.390 | .008 | 45 | -0.344 | .011 |
| Number of lines written | NEO C2 Order | -0.363 | .008 | 52 | -0.346 | .006 |
| Right margin (mean) | NEO C2 Order | 0.361 | .009 | 52 | 0.364 | .004 |
| Number of words | NEO C2 Order | -0.359 | .009 | 52 | -0.383 | .003 |
| Number of ovals | NEO C2 Order | -0.356 | .010 | 52 | -0.348 | .006 |
| Number of lower loops | NEO E5 Excitement-seeking | -0.377 | .010 | 46 | -0.484 | < .001 |
| Line direction (rising) | NEO A4 Compliance | 0.354 | .010 | 52 | 0.273 | .026 |
| Top margin | NEO A1 Trust | -0.354 | .010 | 52 | -0.312 | .013 |
| Bottom margin | NEO O6 Values | -0.354 | .010 | 52 | -0.259 | .033 |
| Lower loop width | MBTI: Thinking (vs. Feeling) | -0.318 | .011 | 63 | -0.372 | .001 |
| Percentage of black pixels (ink density) | NEO O6 Values | 0.346 | .012 | 52 | 0.416 | .001 |
| Oval height, right half | NEO O2 Aesthetics | -0.339 | .014 | 52 | -0.371 | .004 |
| Oval height, upper half | NEO C5 Self-discipline | 0.339 | .014 | 52 | 0.346 | .006 |
| Oval height, upper half | NEO: Conscientiousness | 0.339 | .014 | 52 | 0.312 | .013 |
| Oval height, upper half | NEO O2 Aesthetics | -0.338 | .014 | 52 | -0.321 | .011 |
| Right margin (mean) | MBTI: Extraversion (vs. Introversion) | -0.305 | .014 | 64 | -0.259 | .019 |
| Slant variability | NEO: Extraversion | 0.333 | .016 | 52 | 0.241 | .044 |
| Lower loop width | NEO O6 Values | -0.335 | .016 | 51 | -0.283 | .023 |
| Number of lines written | NEO O1 Fantasy | 0.330 | .017 | 52 | 0.361 | .005 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Oval height, upper half | NEO N6 Vulnerability | -0.329 | .017 | 52 | -0.293 | .018 |
| Oval shape (height/width) | NEO E5 Excitement-seeking | 0.328 | .018 | 52 | 0.323 | .010 |
| Lower loop height/width | NEO A3 Altruism | -0.348 | .018 | 46 | -0.359 | .008 |

Ordered by significance in the Spearman analysis. Only pairings with $p < .05$ in both analyses and the same sign are included. This list is exploratory: without correction for multiple comparisons, some of these associations may be due to chance, and it should be used to formulate hypotheses, not to confirm them. NEO labels follow the international facet names (O = Openness, A = Agreeableness, C = Conscientiousness).

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