Handwriting and Drawing Features for Detecting Personality Traits

Anna Esposito*, Terry Amorese*, Michele Buonanno*, Marialucia Cuciniello*, Antonietta M. Esposito†,
Marcos Faundez-Zanuy‡, Laurence Likforman-Sulem§, Maria Teresa Riviello*, Alda Troncone*, and Gennaro Cordasco*
* Department of Psychology, Università degli Studi della Campania "L. Vanvitelli", and
International Institute for Advanced Scientific Studies (IIASS), Italy, Email:anna.esposito@unicampania.it.
† Istituto Nazionale di Geofisica e Vulcanologia, Sez. di Napoli Osservatorio Vesuviano, Italy.
‡ Escola Superior Politecnica, TecnoCampus Mataro-Maresme, 08302 Mataro, Spain.
§ Télécom ParisTech, Université Paris-Saclay, 75013 Paris, France.

***Abstract*—This research reports on handwriting/drawing quantitative features and their links with personality traits. To this aim, handwriting/drawing tasks have been proposed to 78 subjects (equally balance by gender and aged between 22-35 years), which were first administered the Big Five Personality questionnaire (BFQ). Subjects were clustered as low, typical, and high according to the scores obtained to each 5 personality dimensions (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism). Measures of pressure, ductus, time, space, and inclination, were computed from digital recordings of the proposed handwriting/drawing tasks through an INTUOS WACOM digitizing tablet. On these data, ANOVA repeated measures were performed with gender and group category (low, typical and high for each of the BFQ dimension) as between and associated computed measures as within factors. Results show significant differences for each of the BFQ dimension among subject group categories and handwriting/drawing measures connecting quantitatively personality traits to graphology.**

I. Introduction

Personality refers to the characteristic way of thinking, feeling, and behaving of a given person. Scientists have developed several theories on this psychological concept [1], [2], [3], [4], and "although no single definition is acceptable to all personality theorists, we can say that personality is a pattern of relatively permanent traits and unique characteristics that give both consistency and individuality to a person's behavior" [5]. Personality includes thoughts, emotions and attitudes, both innate and learnt, influencing individuals "interactions with, and adaptations to, the intrapsychic, physical, and social environments" [6].

Tests have been proposed, to measure individuals personality styles, providing a tool for helping people, among other, to know more about themselves, assert their needs, understand their strengths and weakness, connect and create relationships, support their decision makings, identify (for cure) possible mental illnesses. The administration of these tests are regulated by ethical laws, however, it is clear that the detection of personality traits can be crucial for applications in many areas ranging from marketing [7] to health care [8].

One of the most accepted empirically-based model to describe individuals personality traits is the Five Factors Model, also known as the Big Five questionnaire [9], [10], [11]. According to this model, there are five basic traits of human personality: Openness to Experience, Conscientiousness Extraversion, Agreeableness, and Neuroticism (expressed by the acronym, OCEAN). These dimensions do not represent a particular theoretical perspective but were derived from analyses of the natural language terms people use to describe themselves and others. The five dimensions are measured on a continuum, and for each trait, individuals personality stays somewhere on the spectrum, according to the scores on a questionnaire of 132 items. A detailed description of the Big Five Questionnaire (BFQ) is reported in section II.

This model is effectively exploited for a wide range of purposes. In [12], it was proposed to be used as inexpensive and accessible tool to personalize preventive medicine, since it helped health care professionals to identify which young adults would be at greater risk for poor health as they entered midlife. Authors in [13], investigating the relation between supervisors personality traits and employees experiences of supervisory abuse, found a positive relation between supervisors conscientiousness and abusive supervision. According to [14] emotional stability and extroversion in salespeoples personality are the right traits for success. University students high scores in conscientiousness dimension of the Big Five can predict learning and academic achievement [15].

Personality traits can be also deduced through persons handwriting analyses [16]. Handwriting is a creative process which involves conscious and unconscious brain functionalities [17]. Handwriting and drawing analyses have been used for impairment detection and personality trait assessment [18], [19], [20], [21] as well as for the recognition of emotions [22], [23], [24], [25], [26]. To this aim, several tests like the clock drawing test (CDT) [27], the mini mental state examination (MMSE) [28] and the house-tree-person (HTP) [29] have been designed in the medical domain. Handwriting and drawing tasks are typically recorded through a digitizing tablet. Records consist in pen positions, pen states (on-paper and in-air), time stamps, pen pressure and inclination.

The present study proposes to investigate the relation among handwriting features and specific traits of the Big Five model. A similar study has been conducted in [30] where a qualitative analysis of handwriting is used to foresee Big Five personality traits. The study is based on a static analysis of handwriting, which enable to reach an good level of accuracy. In this paper it is adopted a dynamic analysis (see Section II) approach based on quantitative (i.e., objective) and easy computable features. Moreover the analysis considers also the drawing.

II. Handwriting analysis for the detection of personal traits

A. Handwriting Analysis

Recently, thanks to the development of novel technological tools (scanners, touch displays, display pens and graphic tablets), it is possible to perform handwriting analyses on computerized platforms. Such computerized analyses provide two main advantages: i) the collection of data includes several non-visible features such as pressure, pen inclination, in air motions; ii) data includes timing information which enable the *online* analysis the whole drawing and/or handwriting process instead of analyzing a single *offline* snapshot representing the final drawing. Accordingly tests for detecting brain stroke risk factors and disorders, or dementia, have been computerized [27], [31], [32].

Handwriting analysis have been carried out using an INTUOS WACOM series 4 digitizing tablet and a special writing device named Intuos Inkpen. The tablet enables to capture digital signals, which are visualized on the screen and at the same time the inkpen enables the user to visualize the strokes on the the paper (DIN A4 normal paper) laid on the tablet. The system has the nice property to capture in-air movements (that is when the inkpen is very close to the paper).

During each experimental task, the following information is continuously captured with a frequency of 125 Hz:

1) position in x-axis;
2) position in y-axis;
3) time stamp;
4) pen status (in air = 0 or down = 1);
5) azimuth angle of the pen with respect to the tablet;
6) altitude angle of the pen with respect to the tablet;
7) pressure applied by the pen on the paper.

Digital signals are stored in a comma separated values (CSV) file.

B. Personal traits: The Big Five Questionnaire

BFQ identifies five fundamental dimensions for individuals personality description and assessment. Each of them considers two sub-dimensions. Each sub-dimension consists of 12 items, 6 formulated in a positive sense and 6 in a negative sense, in order to control response-set phenomena (i.e. the tendency for a person to respond to questions in such a way that it produces a certain image of her/himself, rather than answering based on the her/his true feelings or behaviors). BFQ also includes a Lie scale (L) which aims to measure the subject's tendency to provide a false profile, both in positive and negative sense. The scale L consists of 12 items referring to socially very desirable behaviors, so that answers of strong agreement or disagreement result highly unlikely. Then, BFQ is made up of a total of 132 items, each requiring an answer that goes from 1-strongly disagree, to 5-strongly agree. The Big Five dimensions and sub-dimensions are described below:

1. Openness to Experience: refers to peoples ability and tendency to explore and create new experiences, manifesting curiosity, imagination, creativity, appreciation for art, and out-of-the-box ideas. The two sub-dimensions are: Intellect and Openness. On this scale, people are rated based on the dichotomy: inventive/curious (higher scores) vs. consistent/cautious (lower scores).

2. Conscientiousness: refers to people who are careful, thorough, responsible, organized, hardworking, achievement-oriented, and persevering. Consciousnesss sub-dimensions are: Industriousness and Orderliness. On this scale, people are rated based on the dichotomy: efficient/organized (higher scores) vs. easy-going/careless (lower scores).

3. Extraversion: refers to people who easily express positive emotions, who are sociable, gregarious assertive, talkative, and active. The two sub-dimensions are: Enthusiasm and Assertiveness. On this scale, people are rated on the dichotomy: outgoing/energetic (higher scores) vs. solitary/reserved (lower scores).

4. Agreeableness: refers to people who have a tendency to be sympathetic, trusting as well as helpful, flexible and tolerant. Agreeableness sub-dimensions are: Compassion and Politeness. On this scale, people are rated based on the dichotomy: friendly/compassionate (higher scores) vs. alleging/detached (lower scores).

5. Neuroticism: refers to people who lack emotional stability and control, and tend to be emotional, anxious, depressed, angry, worried, and insecure. Neuroticisms sub-dimensions are: Withdrawal and Volatility. On this scale, people are rated based on the dichotomy: sensitive/nervous (higher scores) vs. secure/confident (lower scores).

III. The experiment

A. Participants

A total of 78 participants (40 males and 38 females, mean age: 24.6, SD: 2.4) was involved in the experiment. Participants were voluntarily recruited at Università della Campania "Luigi Vanvitelli' in Caserta (south Italy). They were first administered with the Big Five Questionnaire and then they were asked to perform the 7 tasks described in the following.

B. Procedure and Methods

For each Big Five dimension, the participants were partitioned into three different group based on the obtained scores at the questionnaire: specifically, a score less than or equal to 45 was categorized as "low", a score between 46 and 54 was categorized as "typical", and a score greater than 54 was categorized as "high". Table I shows the distribution of participants according to the categories defined above.

	High		Typical		Low	
	F	M	F	M	F	M
Extraversion	17	16	13	17	8	7
Agreeableness	12	18	8	14	18	8
Conscientiosness	16	16	5	14	7	10
Neuroticism	7	14	18	15	13	11
Openness to Experience	16	27	14	9	8	4

TABLE I. *For each of Big Five dimension, the table reports the participant distribution with respect to gender and group.*

The tasks acquired by the tablet are the following:

1) copy of a two-pentagon drawing;
2) copy of a house drawing;

3) writing of four Italian words in capital letters (BIOEGRADABILE (biodegradable), FLIPSTRIM (flipstrim), SMINUZZAVANO (to crumble), CHIUNQUE (anyone));
4) loops with left hand;
5) loops with right hand;
6) clock drawing;
7) writing of the following phonetically complete Italian sentence in cursive letters (I pazzi chiedono fiori viola, acqua da bere, tempo per sognare : Crazy people are seeking for purple flowers, drinking water and dreaming time).

Fig. 1 shows the sample acquired from one participant.

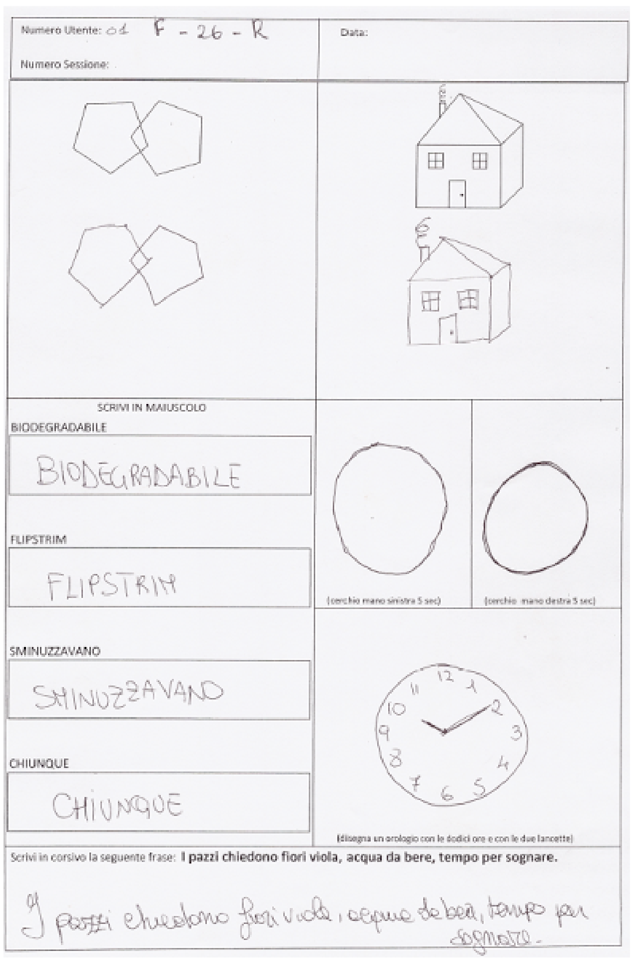

Fig. 1. A4 sheet with the set of tasks filled by one participant.

Using this set of dynamic data, further information such as acceleration, velocity, instantaneous trajectory angle, instantaneous displacement, time features, and ductus-based features can be inferred. Moreover, in this paper we adopt the approach defined in [26] partitioning the pen states into three categories:

- **up**, recorded with state 0;
- **down**, recorded with state 1;
- **idle**, not recorded but recognizable using time stamps.

Specifically, we considered 17 features grouped into 5 categories:

Pressure, based on the pressure applied by the pen on the paper during a specific task. :

1) P_{min}, minimum pressure;
2) P_{max}, maximum pressure;
3) P_{avg}, average pressure;
4) P_{sd}, standard deviation of pressures;
5) P_{10}, 10^{th} percentile;
6) P_{90}, 90^{th} percentile.

Ductus, based on the number of strokes, in each pen state, performed during the task:

7) N_{up}, number of in air strokes;
8) N_{down}, number of on paper strokes;
9) N_{idle}, number of idle strokes (strokes away from the tablet).

Time, based on the time spent, in each pen state, to complete the task:

10) T_{up}, time spent on in air strokes;
11) T_{down}, time spend on on paper strokes;
12) T_{idle}, time spent in the idle state;
13) T_{total}, total time elapsed for the task.

Space, based on the space used by the strokes:

14) S_{bb}, sum of spaces used by on paper strokes. For each stroke we compute the smallest axis aligned box containing the stroke and sum its area;
15) S_{avg}, average lengths of empty spaces between consecutive on paper strokes;
16) S_{total}, sum of the lengths of empty spaces between consecutive on paper strokes.

Inclination, based on the inclination of strokes:

17) I_{avg}, average inclination of on paper strokes.

IV. RESULTS

Results are computed through different repeated measure ANOVA analyses. In particular, an ANOVA was performed for each group of handwriting features (category) and for each handwriting task. Each ANOVA considers participants gender and big five dimensions group (e.g., low, typical and high) as between subjects factors, whereas participant's scores on each handwriting feature, belonging to the considered category, as within subjects factors. For instance, the ANOVA for the category *Pressure* and the Task 1 (e.g., *Copy of a two-pentagon drawing*) uses the six pressure features scores (e.g., P_{min}, P_{max}, P_{avg}, P_{sd}, P_{10} and P_{90}) computed on the data acquired during the task 1 as within subjects factors.

In the following, for each category, the significant results (significance level was set at $\alpha = .05$) are presented:

A. Pressure

1) Openness to Experience:

a) Task 3: Writing in capital letters: It exists a significant difference among groups $[F(2, 72) = 4.463, p = 0.015]$. Bonferroni post hoc analysis reveals that participants belonging to the *low* group ($M = 424.262, SD = 24.145$) differ significantly ($p = 0.024$) with respect to participants belonging to the *high* group ($M = 341.317, SD = 16.846$). In particular, this difference is due to the scores in the following features:

- P_{max}: The *low* group ($M = 514.53, SD = 99.84$) differs significantly ($p = 0.012$) with respect to the *typical* group ($M = 402.57, SD = 95.03$);
- P_{sd}: The *low* group ($M = 165.66, SD = 13.91$) differs significantly ($p = 0.045$) with respect to the *typical* group ($M = 143.65, SD = 22.93$);
- P_{10}: The *low* group ($M = 273.25, SD = 97.52$) differs significantly ($p = 0.013$) with respect to the *typical* group ($M = 191.26, SD = 69.73$);
- P_{90}: The *low* group ($M = 698.92, SD = 108.66$) differs significantly ($p = 0.011$) with respect to the *typical* group ($M = 576.74, SD = 110.61$);

B. Ductus

1) Agreeableness:

a) Task 1: Copy of a two-pentagon drawing: It exists a significant difference among groups [$F(2, 72) = 5.489, p = 0.006$]. Bonferroni post hoc analysis reveals that participants belonging to the *low* group ($M = 6.72, SD = 1.54$) differ significantly with respect to

- ($p = 0.015$) participants belonging to the *high* group ($M = 12.94, SD = 1.35$);
- ($p = 0.006$) participants belonging to the *typical* group ($M = 12.78, SD = 1.60$).

b) Task 2: Copy of a house drawing: It exists a significant difference among groups [$F(2, 72) = 4.511, p = 0.014$]. Bonferroni post hoc analysis reveals that participants belonging to the *low* group ($M = 18.32, SD = 2.42$) differ significantly with respect to

- ($p = 0.009$) participants belonging to the *high* group ($M = 27.88, SD = 2.12$);
- ($p = 0.043$) participants belonging to the *typical* group ($M = 25.18, SD = 2.52$).

c) Task 3: Writing in capital letters: It exists a significant difference among groups [$F(2, 72) = 6.619, p = 0.002$]. Bonferroni post hoc analysis reveals that participants belonging to the *low* group ($M = 40.87, SD = 1.16$) differ significantly ($p = 0.043$) with respect to participants belonging to the *high* group ($M = 46.50, SD = 1.02$).

d) Task 6: Clock drawing: It exists a significant difference among groups [$F(2, 72) = 5.299, p = 0.007$]. Bonferroni post hoc analysis reveals that participants belonging to the *low* group ($M = 20.78, SD = 1.71$) differ significantly ($p = 0.001$) with respect to participants belonging to the *high* group ($M = 28.18, SD = 1.48$). This difference is due to the scores in the N_{idle} feature: The *low* group ($M = 14.00, SD = 12.09$) differs significantly ($p = 0.04$) with respect to the *high* group ($M = 29.50, SD = 19.42$).

2) Conscientiosness:

a) Task 1: Copy of a two-pentagon drawing: It exists a significant difference among groups [$F(2, 72) = 5.056, p = 0.009$]. Bonferroni post hoc analysis reveals that participants belonging to the *low* group ($M = 6.34, SD = 1.91$) differ significantly ($p = 0.011$) with respect to the *high* group ($M = 13.58, SD = 1.37$).

b) Task 2: Copy of a house drawing: It exists a significant difference among groups [$F(2, 72) = 6.766, p = 0.002$]. Bonferroni post hoc analysis reveals that participants belonging to the *high* group ($M = 29.37, SD = 2.01$) differ significantly with respect to

- ($p = 0.007$) participants belonging to the *low* group ($M = 18.03, SD = 2.81$);
- ($p = 0.007$) participants belonging to the *typical* group ($M = 21.03, SD = 2.12$).

c) Task 6: Clock drawing: It exists a significant difference among groups [$F(2, 72) = 3.685, p = 0.030$]. Bonferroni post hoc analysis reveals that participants belonging to the *high* group ($M = 27.67, SD = 1.45$) differ significantly ($p = 0.028$) with respect to the *typical* group ($M = 22.04, SD = 1.53$).

3) Openness to Experience:

a) Task 3: Writing in capital letters: It exists a significant difference among groups [$F(2, 72) = 4.253, p = 0.018$]. Bonferroni post hoc analysis reveals that participants belonging to the *low* group ($M = 39.47, SD = 1.72$) differ significantly ($p = 0.038$) with respect to the *high* group ($M = 44.93, SD = 0.89$).

b) Writing a sentence in cursive letters: It exists a significant difference among groups [$F(2, 72) = 4.292, p = 0.017$]. Bonferroni post hoc analysis reveals that participants belonging to the *low* group ($M = 25.64, SD = 2.39$) differ significantly with respect to

- ($p = 0.026$) participants belonging to the *high* group ($M = 32.64.03, SD = 1.23$);
- ($p = 0.037$) participants belonging to the *typical* group ($M = 33.90, SD = 1.67$).

C. Time

1) Extraversion:

a) Task 4: Loops with left hand: It exists a significant difference among groups [$F(2, 72) = 4.561, p = 0.014$]. Bonferroni post hoc analysis reveals that participants belonging to the *low* group ($M = 3624.54, SD = 517.17$) differ significantly ($p = 0.010$) with respect to participants belonging to the *high* group ($M = 5490.29, SD = 348.06$). In particular, this difference is due to the scores in the following features:

- T_{down}: The *low* group ($M = 6748.60, SD = 3930.590$) differs significantly ($p = 0.004$) with respect to the *high* group ($M = 10593.79, SD = 3091.29$).
- T_{total}: The *low* group ($M = 7216.53, SD = 4309.84$) differs significantly ($p = 0.011$) with respect to the *high* group ($M = 11011.18, SD = 3105.21$);

b) Task 5: Loops with right hand: It exists a significant difference among groups [$F(2, 72) = 4.411, p = 0.016$]. Bonferroni post hoc analysis reveals that participants belonging to the *low* group ($M = 3400.26, SD = 398.02$) differ significantly ($p = 0.012$) with respect to participants belonging to the *high* group ($M = 4805.20, SD = 267.87$). In particular, this difference is due to the scores in the following features:

- T_{down}: The *low* group ($M = 6345.40, SD = 3778.45$) differs significantly ($p = 0.003$) with respect to the *high* group ($M = 9623.30, SD = 2794.69$).
- T_{total}: The *low* group ($M = 6781.27, SD = 4086.92$) differs significantly ($p = 0.014$) with respect to the *high* group ($M = 9642.70, SD = 2809.08$);

2) Agreeableness:

a) Task 2: Copy of a house drawing: It exists a significant difference among groups [$F(2, 72) = 3.203, p = 0.046$]. Bonferroni post hoc analysis reveals that participants belonging to the *low* group ($M = 14694.40, SD = 1658.20$) differ significantly ($p = 0.027$) with respect to participants belonging to the *high* group ($M = 20133.87, SD = 1454.34$). In particular, this difference is due to the scores in the T_{total}g features: The *low* group ($M = 28952.31, SD = 6484.30$) differs significantly ($p = 0.048$) with respect to the *high* group ($M = 40179.33, SD = 13176.61$).

3) Conscientiousness:

a) Task 5: Loops with right hand: It exists a significant difference among groups [$F(2, 72) = 5.212, p = 0.008$]. Bonferroni post hoc analysis reveals that participants belonging to the *high* group ($M = 5089.42, SD = 268.34$) differ significantly with respect to

- ($p = 0.046$) participants belonging to the *low* group ($M = 3962.11, SD = 374.04$);
- ($p = 0.015$) participants belonging to the *typical* group ($M = 3956.29, SD = 282.05$).

In particular, these difference are due to the scores in the following features:

- T_{down}: The *high* group ($10158, 84, SD = 2440.62$) differs significantly ($p = 0.049$) with respect to the *low* group ($M = 7913.82, SD = 4036.20$) and differs significantly ($p = 0.006$) with respect to the *typical* group ($M = 7691.21, SD = 3041.55$);
- T_{total}: The *high* group ($M = 10178.84, SD = 2453.10$) differs significantly ($p = 0.014$) with respect to the *typical* group ($M = 7916.66, SD = 3144.01$).

4) Openness to Experience:

a) Task 4: Loops with left hand: It exists a significant difference among groups [$F(2, 72) = 4.274, p = 0.018$]. Bonferroni post hoc analysis reveals that participants belonging to the *low* group ($M = 3498.84, SD = 620.43$) differ significantly ($p = 0.017$) with respect to participants belonging to the *high* group ($M = 5513.23, SD = 319.64$). In particular, this difference is due to the scores in the following features:

- T_{down}: The *low* group ($M = 6577.75, SD = 4968.63$) differs significantly ($p = 0.004$) with respect to the *high* group ($M = 10310.23, SD = 3541.46$).
- T_{total}: The *low* group ($M = 7096.92, SD = 5318.63$) differs significantly ($p = 0.015$) with respect to the *high* group ($M = 10867.05, SD = 3913.66$);

b) Task 5: Loops with right hand: It exists a significant difference among groups [$F(2, 72) = 6.588, p = 0.002$]. Bonferroni post hoc analysis reveals that participants belonging to the *low* group ($M = 2997.26, SD = 458.12$) differ significantly with respect to

- ($p = 0.003$) with respect to participants belonging to the *high* group ($M = 4868.37, SD = 236.02$);
- ($p = 0.016$) participants belonging to the *typical* group ($M = 4488.11, SD = 319.63$).

In particular, these differences are due to the scores in the following features:

- T_{down}: The *low* group ($M = 6016.33, SD = 4013.16$) differs significantly ($p = 0.001$) with respect to the *high* group ($M = 9433.81, SD = 2595.61$) and differs significantly ($p = 0.036$) with respect to the *typical* group ($M = 8904.91, SD = 3315.25$);
- T_{total}: The *low* group ($M = 6082.58, SD = 4044.37$) differs significantly ($p = 0.002$) with respect to the *high* group ($M = 9448.70, SD = 2608.53$) and differs significantly ($p = 0.028$) with respect to the *typical* group ($M = 9154.61, SD = 3340.41$).

D. Space

1) Agreeableness:

a) Writing a sentence in cursive letters: It exists a significant difference among groups [$F(2, 72) = 3.779, p = 0.027$]. Bonferroni post hoc analysis reveals that participants belonging to the *low* group ($M = 46578.17, SD = 3199.06$) differ significantly ($p = 0.039$) with respect to participants belonging to the *typical* group ($M = 34025.13, SD = 3336.71$). This difference is due to the scores in the S_{bb} features: The *low* group ($M = 100358.04, SD = 34031.33$) differs significantly ($p = 0.018$) with respect to the *typical* group ($M = 73902.36, SD = 22654.32$)

2) Neuroticism:

a) Task 2: Copy of a house drawing: It exists a significant difference among groups [$F(2, 72) = 5.173, p = 0.008$]. Bonferroni post hoc analysis reveals that participants belonging to the *high* group ($M = 36561.59, SD = 1640.86$) differ significantly with respect to

- ($p = 0.027$) participants belonging to the *low* group ($M = 30081.00, SD = 1452.15$);
- ($p = 0.031$) participants belonging to the *typical* group ($M = 30890.02, SD = 1239.22$).

3) Openness to Experience:

a) Task 3: Writing in capital letters: It exists a significant difference among groups [$F(2, 72) = 4.772, p = 0.011$]. Bonferroni post hoc analysis reveals that participants belonging to the *low* group ($M = 49467.81, SD = 4526.06$) differ significantly ($p = 0.010$) with respect to the *typical* group ($M = 33380.79, SD = 3157.78$). In particular, this difference is due to the scores in the following features:

- S_{bb}: The *low* group ($M = 112185.00, SD = 30605.94$) differs significantly ($p = 0.003$) with respect to the *typical* group ($M = 71987.74, SD = 31100.25$) ;
- S_{avgl}: The *low* group ($M = 1068.92, SD = 459.25$) differs significantly ($p = 0.048$) with respect to the *typical* group ($M = 702.00, SD = 304.99$) .

E. Inclination

No significant results have been identified with respect to the Inclination feature. However, a preliminary analysis has shown that this feature can be useful to identify *Volatility*, a sub-dimension of Neuroticism.

V. Conclusion

The statistical analysis, carried out using the repeated measure ANOVA, shows that it is possible to discriminate between different personality traits (dimensions of the Big-Five) using quantitative data about writing and drawing simple tasks.

Considering the positive results achieved, it would be interesting to analyse the interaction between the considered features and the Big Five traits sub-dimensions.

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