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An Empirical Study On Personality Identification Through Handwritten Signature Analysis Among College Students In Bangalore

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Abstract
Graphology, the study of handwriting to infer personality, has long been controversial due to contradicting scientific data. Despite the fact that thorough research on signatures is still sparse, particularly in non-western contexts, these deliberate and persistent self- expressions may offer distinctive insights on personality. This study examines the connections between nine trademark signature traits and NEO-Five Factor Inventory personality domains in Bangalore college students. A sample of 117 individuals between the ages of 18- 26 completed the NEO- Five Factor Inventory. A defined procedure was used to code signature features, such as curved start, ending stroke, shell signature, middle stroke, underlining, upper stroke, slant, letter connections, and baseline directions. To test associations, Spearman's rank correlations were computed. Moderate but significant correlations were found. Extraversion had a negative correlation with baseline direction and end stroke and a positive correlation with underlining use. Neuroticism had a negative correlation with upper stroke and a positive correlation with shell signature. Curved start was negatively correlated with conscientiousness. There were no significant correlations between agreeableness and openness. The findings provide limited support for graphological validations, with effect sizes comparable with meta- analytic data supporting some signature- personality relationships. When employed, signature- based personality assessment should only be used as an add-on to more comprehensive assessment frameworks.

Keywords: *Graphological Variables; Handwritten Signature Analysis; NEO- FFI; Personality Identification*

1. Introduction
For more than a century, academics, professionals, and laypeople have been fascinated by the connection between human handwriting and personality. The process of analyzing handwriting features in an effort to determine psychological attributes is known as graphology, and it has historically been used in fields like forensic investigation, counseling, and hiring. According to graphological theory, each person's handwriting is a complicated motor action influenced by their own neurological and psychological processes [1]. According to Pandey and Ansari (2024), handwriting is "the combination of mental and muscular deviation resulting in a neuromuscular reaction and giving the writing its individuality," implying that each person's distinct handwriting may contain significant personal information [2]. Within the scientific community, there is still much disagreement over the empirical validity of graphological assertions despite their extensive use and ongoing popular appeal [3, 4]. For decades, the profession has been marked by a conflict between enthusiastic practice and skeptical scrutiny, with academics advocating for thorough, methodologically sound investigations, to distinguish between claims that are unsupported by empirical evidence and those that are not. The scientific study of the connections between personality and handwriting has a long history. According to Mailhos et al. (2016), early empirical studies, such as Hull and Montgomery's 1919 study, found little evidence connecting particular handwriting traits to personality traits. When Crider (1941) investigated

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the validity and reliability of graphologists' assessments, he found little proof that graphological assessments are accurate. In a similar vein, Fluckinger, Tripp, and Weinberg (1961) carried out a thorough analysis of nearly thirty years' worth of experimental graphology research and came to the conclusion that the data did not substantiate compelling arguments for graphological validity [3]. The late twentieth century saw the emergence of the most significant and methodologically rigorous criticisms. In a major meta- analysis of the predictive validity of graphological findings, a large meta-analytic investigation by Neter and Ben-Shakhar (1989) evaluated seventeen studies in which both professional graphologists and non- experts attempted to determine personality from more than a thousand handwriting samples. When evaluations were carried out by qualified graphologists, the reported effect sizes were incredibly tiny and correlations remained near zero. Crucially, the validity of graphologists neared zero when neutral scripts where handwriting samples were devoid of meaningful content were employed [5]. The results implied that whatever limited validity found in graphological evaluations might come from the writings semantic content rather than from graphological characteristics in and of themselves. Additionally, psychologists without graphology experience did better than graphologists on every metric, raising serious concerns about the special value of graphological expertise [6]. Similar results were previously reported by Ben- Shakhar and colleagues (1986) in two empirical investigations looking at graphology's capacity to predict occupational success, which they described as "methodological ruminations" on the shortcomings of handwriting analysis [7]. Kilmoski and Rafaeli (1983) also looked into using handwriting analysis to infer human traits, however they found no evidence to support graphological conclusions [8]. Theoretical frameworks have been established to explain the potential relationship between handwriting and personality, despite ongoing skepticism. According to modern researchers, handwriting is an example of how physical, emotional and cognitive processes are integrated. Gawda (2014) found minimal significant connections between handwriting dimensions and personality traits as measured by NEO- FFI and EPQ-R, and concluded that there was little evidence to support the use of handwriting analysis for personality trait evaluation [9]. Even while direct trait prediction is still difficult, Gawda's later work (2019) suggested a network model that links graphical expression to mental representation of self and emotion, implying that handwriting may reflect stable individual differences in psychomotor expression [10]. Relationships between personality and handwriting are plausibly explained by the brain foundations of handwriting. The motor cortex, basal ganglia, cerebellum, and association areas involved in planning and execution are only a few of the brain regions involved in the intricate motor skill of handwriting. Personality traits may have an impact on the fine motor control that underpins graphic production through these brain systems, which are impacted by limbic and cortical circuits involved in emotional processing and self- representation. Features including baseline, slant, size, spacing, margin, and pressure may be markers of underlying psychological traits, according to Pandey and Ansari (2024), who highlight how handwriting characteristics can disclose parts of personality, behavior, and even psychiatric symptoms [2]. Their work contributes to the ongoing endeavor to find empirically validated connections between handwriting characteristics and personality traits by offering an overview of forensic graphology and review of literature. In the twenty-first century, there has been a resurgence of interest in rigorous scientific studies of the connections between personality and handwriting. A quantitative study by Čálková (2025) examined the connection between the personality factors outlined in the NEO big five model and geographical characters such as writing size, slant, and width. In order to identify important associations, the study analyzed 31 master's students' articles using descriptive statistics, Pearson's correlation coefficients, and linear regression analysis. Despite the small sample size, this study advanced knowledge of graphology's potential as a tool for evaluating personality traits in HRM settings [11]. Although graphological theory suggests that a wide range of

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stroke qualities can reflect psychological traits, Chaudhari and Desai (2024) conducted a thorough survey on decoding personalities through handwriting analysis, pointing out that prior research has concentrated on a limited number of handwriting characteristics, their review highlights the significance of bridging gaps between personality psychology and graphology by examining different approaches for feature extraction to predict personality based on handwriting. They promote computer based graphology as a technique for personality prediction, arguing that psychologically supported handwriting qualities can help predict personality traits [3]. The capacity of handwriting analysis to evaluate Big Five Personality traits was not supported by Dazzi and Pedrabissi's (2009) empirical investigation that looked at relationships between the Big Five Questionnaire and graphological evaluations. This study added to the increasing amount of data indicating the standard graphological claims might not be supported by empirical data [4]. Recent research has increasingly turned to computational approaches using automated algorithms and deep learning models, to evaluate handwriting patterns more objectively. Ahirwar and associates (2026) offer a thorough examination of this paradigm change, following the development from conventional graphology to contemporary methods utilizing sophisticated deep learning algorithms and automated feature extraction. Through a critical analysis of the history of personality predicting through handwriting investigation, their study documents the increasing competence of automated systems in comparison to traditional methods [12]. Several shortcomings of conventional graphological studies are addressed by this computational turn. Machine learning techniques can extract and analyze hundreds of features simultaneously, potentially revealing patterns that are imperceptible to human sight. Large data sets with proven ground truth (such as standardized personality tests) can be used to train them, allowing for the creation of predictive models with measurable accuracy. Computational methods enable thorough cross- validation and the methodical analysis of feature significance, which may reveal which handwriting traits genuinely influence personality direction. Ahirwar and colleagues (2026) list important obstacles that this multidisciplinary discipline must overcome, such as unbalanced data, interpretability issues with models, computing demands, ethical issues, and the limitations of applying these technologies in practical contexts. Their work highlights the necessity of ongoing research addressing these issues and underscores the significance of creating reliable, egalitarian, and advantageous diagnostic technologies [12]. Shevchenko and Shevchenko (2025) divided handwriting analysis techniques into four categories, emphasizing the benefits and drawbacks of each strategy while addressing a number of issues related to creating handwriting analysis systems, including incorrect feature extraction, over fitting, under fitting, unreliable training data, and model selection for personality type assessment. In addition to standard techniques for performance evaluation and database selection, their review included techniques for reliable offline writer identification, as well as techniques for human personality prediction utilized in cutting-edge handwriting analysis systems [13]. Using a heterogeneous dataset of 1108 handwriting picture samples, Singh and Rani (2025) investigated the merging of graphology and machine learning to analyze personality traits through handwriting. Using stacking ensemble approaches, their experimental results showed a considerable boost in prediction accuracy, surpassing 90% for qualities like "Agreeableness" and "Openness to Experience." This study showed how interdisciplinary approaches that combine traditional graphological methods with modern machine learning techniques can improve the accuracy of personality trait prediction [14]. Gavrilescu and Vizireanu (2018) showed that automated analysis could find systematic relationships between graphical features and personality dimensions by creating a system for predicting the Big Five Personality traits from handwriting using machine learning techniques [15]. While Fatimah and colleagues (2019) used convolutional neural networks to identify personality traits from handwriting [16], Joshi and colleagues(2018) used machine learning techniques

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to assess employability through handwriting analysis [17]. Signatures have a special psychological value as unique forms of self- expression, even though a lot of handwriting research has concentrated on general handwriting samples. Signatures are deliberately created and regularly replicated over time, in contrast to normal handwriting, which is usually made for communication purposes with various degrees of attention to form. Signatures may be particularly informative of personality and self-concept due to their intentionality and consistency. In a thorough investigation of a sample Uruguayan university students (N = 340), Mailhos and colleagues (2016) examined the association between signature size and personality qualities such as intrasexual competitiveness, aggressive and social dominance, narcissism and self-esteem. By analyzing three distinct operationalizations of signature size and accounting for potential confounders such as the number of characters in a printed name, average character area in a printed name (a proxy for overall writing size), and signature style, the study methodologically went beyond the previous research. Once these factors were taken into account, the findings revealed that sociable dominance and signature size were highly correlated in both males and females, whereas narcissism was only significantly correlated in females [18]. Experimental research further supports the psychological impact of signatures. According to Kettle and Häubl (2011), signing one's name can influence future purchasing decisions in areas related to one's self-identity [19]. According to Shu and colleagues (2012), signing at the start of the paper instead of the conclusion reduces dishonest self-reports, presumably by drawing attention to oneself and highlighting moral ideas [20]. These results were expanded upon by Chou (2015), who show that handwritten signatures trigger this effect but e-signatures do not because the latter suggest a reduced sense of self-presence [1]. Signature size arose in comparison to the non-affective control condition after a positive-affect priming task, as demonstrated by Rawal and Colleagues (2014), indicating that temporary affective states can affect signature generation [21].

1.1. Cultural Consideration

Despite the cultural differences in handwriting styles and personality expression, there is still little research on handwriting analysis in non-Western cultures. With its many educational institutions, rich calligraphic traditions, and linguistic diversity, India offers an especially intriguing setting for this kind of study. Bangalore, a significant center for education and technology, has a wide range of students from different language and geographic origins, making it a suitable place for preliminary research while recognizing the necessity of cross- cultural replication. In Bangalore, businesses that provide graphology services and training programs have made handwriting analysis a commercial endeavor. A group of graphologists from Bangalore called Write Strokes does research on handwriting analysis and hosts courses and events throughout the city. Their goal is to promote personality development by providing graphotherapy to both adults and children. Similar to this, training sessions on handwriting analysis are frequently held in Bangalore, emphasizing the use of handwriting analysis to identify personality traits while fusing theoretical knowledge with real- world applications. The importance of empirical study looking at the scientific underpinnings of such activities is shown by this local interest in graphology.

1.2. Research Gaps

There are still a number of important gaps in the literature despite increased study interest and methodological advancements. First, despite theoretical expectations that signatures could be more personally revealing, relatively few researchers have particularly examined signatures as opposed to general handwriting. Signatures and printed names seem to trigger different self- feelings, as highlighted by Mailhos and colleagues (2016) [18]. This suggests that signatures may have special psychological importance that merits further research. Second, despite possible cultural differences in handwriting styles and personality expression, research in non-Western environments, particularly in Indian cultures, is still scarce. An opportunity to investigate whether connections found in Western samples apply to this setting is provided by the Bangalore college

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population. Third, there is a dearth of systematic empirical research employing standardised personality measurements to support many graphological statements about particular stroke qualities, such as curved starts, end strokes, underlines, and letter connections. Other potentially significant characteristics such as stroke complexity, embellishments, baseline orientation, and letter connectedness, have not gotten as much attention in the literature as signature size. Chaudhari and Desai (2024) point out that although empirical research has usually only looked at a small number of variables, graphological theory predicts that a large range of stroke qualities can reflect psychological traits [3]. Fourth, although promising, the shift from classical graphology to computer methods necessitates basic empirical research to determine which traits exhibit trustworthy connections with personality tests. When machine learning models are constructed on feature sets that are well- understood and have clear connections to outcome variables, they perform well. By methodically analyzing relationships between nine trademark traits and NEO-FFI personality factors, the current study adds to this foundational work. The current study examines the correlations between nine trademark traits and NEO-FFI personality domains in Bangalore college students. This study attempts to provide empirical evidence for the validity of signature- based personality assessment by using a co-relational design with strict coding methods and standardized personality measurement.

2. Method

2.1. Participants

Data will be collected from 140 college students across Bangalore using convenience sampling. The sample size was computed based on the study objective. The participants must be between the ages of 18 and 26, enrolled in colleges/ universities across Bangalore, and be able to sign documents naturally without help in order to be eligible. Individuals with any ailment that interferes with normal handwriting skills (such as upper limb injuries or neurological problems) and incomplete questionnaire responses will be excluded.

2.2. Procedure

The study was conducted among college students in Bangalore to examine the relationship between Signatures and Personality traits. Participants were recruited through purposive sampling from various Colleges and Universities in the city. 140 Participants were invited to take part in the study voluntarily and were provided with the forms which included the informed consent form, demographic details, NEO-FFI self- report questionnaire (Costa & McCrae, 1992), and a form for collecting Signatures. The participants completed the form in 15-20 minutes. Prior to analysis, data were screened for missing values and outliers. Out of the 140 data collected, 117 were suitable for analysis. Following data cleaning, statistical analyses were conducted using IBM SPSS (Version 20). Descriptive statistics, Spearman's rank correlation were performed to test the hypothesis.

2.3. Instruments

Neo Five Factor Inventory (NEO-FFI). The 60- item NEO- FFI self- report questionnaire measures the five core personality categories of neuroticism, extraversion, agreeableness, conscientiousness, and openness to new experiences (Costa & McCrae, 1992). Twelve items are used to grade each domain on a 5-point Likert scale ranging from "strongly agree" to "strongly disagree." The NEO-FFI has well- established psychometric properties, such as test- retest reliability exceeding .80 and internal consistency coefficients ranging from .74 to .89 across domains [22]. Signature Collection Protocol Participants will use a normal blue or black point pen to create 10 natural signatures on a plain sheet of paper. They will be told to sign without paying any special regard to style or neatness, just like they would on an official document. To ensure anonymity during analysis, a unique code will be provided to each signature. To account for intra- individual heterogeneity, numerous signatures will be gathered in accordance with Mailhos and colleagues' (2016) methodological approach [18].

Signature Coding Scheme

Nine signature characteristics will be methodically coded based on graphological literature and variables found in current computational studies:

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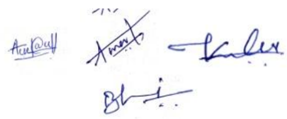
Table 1. Signature Coding Scheme with examples

Name	Description	Coding Categories	Example
S1	Curved Start	Smooth Curved- 2 Backward Curved- 3 Sharp Curved- 4	
S2	Ending Stroke	Ascending Ending Stroke- 2 Descending Ending Stroke- 3 Straight Ending Stroke- 4	
S3	Shell Signature	No Encircle Signature- 1 Encircled Signature- 2	
S4	Middle Stroke	No Middle Stroke- 1 Middle Stroke- 2	
S5	Underline	No Underline Signature- 1 1 Underline Signature- 2 Many Underline Signature- 3	
S6	Upper Stroke	No Upper Strokes- 1 Upper Strokes- 2	
S7	Overall Slant	A: 1 B-C: 2 C-D: 3 D-E: 4 A-F: 5 F-G: 6	
S8	Letter Connections	Angular- 1 Arcade- 2 Garland- 3 Thread- 4	
S9	Baseline Direction	Elevated- 1 Even Mood- 2 Depressed- 3 Starts Well but Regresses- 4	

3. Results And Discussion

3.1. Results

Table 2. Hypothesis testing- Correlation table of the signature characteristics and NEO personality factors

	S1	S2	S3	S4	S5	S6	S7	S8	S9
N	0.038	-0.113	.188*	-0.003	0.002	- .257**	0.108	-0.104	-0.106
E	0.014	-.269**	-0.107	-0.085	.323**	-0.045	0.158	-0.06	-.223*
O	-0.158	-0.07	-0.043	-0.052	-0.063	-0.057	0.116	0.111	-0.063
A	0.005	-0.056	-0.008	0.057	0.088	-0.094	-0.007	0.042	-0.09
C	-.211*	-0.099	0.018	-0.173	-0.025	-0.016	0.044	0.024	-0.142

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The associations between the nine S variables (S1-S9) and the Big Five personality traits (Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness) among 117 people were investigated using a Spearman's rank- order correlation analysis. Neuroticism showed a strong negative correlation with S6 (r_s= -0.257, p <0.01) and a substantial positive correlation with S3 (r_s= 0.188, $p < 0.05$). The positive correlation with S3 implies that people with greater neuroticism scores might also have a shell type of signature, suggesting that this dimension may be connected to emotional instability or stress vulnerability. On the other hand, the negative correlation with S6 implies that people who are more neurotic might not have any upper strokes in their signature. People with higher extraversion tend to prefer ascending ending strokes more, according to a negative correlation with S2 (r_s= -0.269, $p < 0.01$). Additionally, extraversion showed a positive association with S5 (r_s= 0.323, $p < 0.01$), indicating that those who are more gregarious, vivacious, and outgoing might prefer using underlines in their signature. Furthermore, a negative correlation with S9 (r_s= -0.223, $p < 0.05$) suggests that individuals prefer angular letter connections and these may be linked to stronger extraversion. Openness to experience did not exhibit any statistically significant relationships with the signature characteristics. This implies that the dimensions measured by the S variables in this sample may not be strongly or directly related to openness, which is generally associated with curiosity, imagination, and intellectual engagement. Similarly, there were no statistically significant relationships found between agreeableness and the signature characteristics. In every dimension, the associations were negligible and not significant. This suggests that within the current group, there may not be a strong correlation between the conceptions evaluated by these variables and the propensity to be cooperative, sympathetic, and compassionate. Conscientiousness had a substantial negative correlation (r_s= -0.211, $p < 0.05$). This implies that those with greater conscientiousness scores which are marked by responsibility, organization, and self-discipline tend to use a curved start to their signatures. Conscientiousness's role in encouraging self- control and goal- directed behavior, which may lessen inclinations linked to the S1 variable, may be reflected in this relationship.

3.2.Discussion

The current study examined the connections between handwritten signature characteristics and the Big Five personality traits among college students in Bangalore disproving the hypothesis. The results show significant limits in graphological techniques to personality assessment while offering some support for the proposed relationships. Signature traits and Extraversion Extraversion and Underlines (S5) have a positive correlation, which is consistent with both prior empirical research and theoretical predictions. It has long been hypothesized that expansive trademark traits represent outward orientation and social interaction. Larger signatures are linked to higher scores on this dimension, indicating sociable dominance as Mailhos and colleagues (2016) showed [18]. A similar phenomenon may be reflected in the positive correlation shown in this study: extraverted people may create more expansive, eye-catching distinctive pieces. Zweigenhaft's (1970, 1977) seminal work that connected trademark traits to self-esteem and status- seeking behavior is in line with this interpretation [23, 24]. There are more intricate negative associations between extraversion and Ending Strokes (S2) and Baseline Direction (S9). These characteristics seem to access a common underlying dimension, as seen by the high positive correlation between S2 and S9. Their negative correlation with extraversion implies that people with high extraversion may steer clear of some trademark traits, possibly those linked to introspection, retreat, or constraint. This interpretation is consistent with Eysenck's (1990) definition of extraversion, which includes lower inhibition, activity, and sociability [25]. Neuroticism and Signature Traits There is a negative correlation between neuroticism and Upper Stroke (S6) and a positive correlation with Shell Signature (S3). Anxiety, moodiness, and emotional instability are traits of people with high neuroticism. The uneven or unstable stroke patterns that appear in the creation of signatures may be the cause of the positive correlation with S3. On the other hand, the

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negative link with S6 implies that people who are emotionally secure and have low levels of neuroticism may create signatures that are more consistent, regular, or pressure- controlled. These results are consistent with studies that link emotional regulation to handwriting. Conscientiousness and Signatures Highly conscientious people score lower on this specific trait, according to the negative correlation between conscientiousness and Curved Start (S1). Organization, reliability, and self- control are characteristics of conscientiousness. The negative orientation implies that S1 can stand for a trait like carelessness, disorganization, or unconventionality that is at odds with conscientious expression. Agreeableness, Openness to Experience and Signature Traits It is remarkable that there are no significant relationships between Openness and Agreeableness, which is consistent with earlier studies that cast doubt on the reliability of handwriting analysis. According to Dazzi and Pedrabissi (2009), there was no correlation between graphological assessments and the Big Five characteristics as determined by standardized questionnaires. Similar to this, Gawda (2014) found few significant connections between handwriting features and NEO- FFI scores, with the conclusion that there was insufficient evidence to support the use of handwriting analysis for personality assessment [4, 9]. The findings are consistent with the larger body of research on handwriting analysis, showing isolated significant correlations among many non- significant associations. Graphological conclusions showed only limited validity, with correlations ranging from 0.136 to 0.206, according to a meta- analysis by Neter and Ben- shakhar (1989). The current study's impact sizes, which range from 0.188 to 0.323, are similar to those found in the meta- analysis [5]. In handwriting analysis, the shift to computational methods holds promise for resolving some of the shortcomings of conventional graphological study. While Gavrilescu and Vizireanu (2018) reported prediction accuracy of 84.4% for specific features using neural network methodologies, Singh and Rani (2025) achieved high prediction accuracy utilizing stacking ensemble methods [14, 15]. Fatimah and colleagues (2019) used convolutional neural networks to identify personality features with an accuracy of up to 98.03%. These striking numbers should be regarded with caution, though, as machine learning models may not generalize beyond training samples without thorough cross- validation and may profit from random relationships.

3.3.Theoretical Implications

The current research contributes to our theoretical knowledge of handwriting as a behavioral manifestation of personality. The found correlations somewhat corroborate Gawda's (2019) network model, which views handwriting as combining cognitive, emotional, and motor components. In line with the idea that neural systems involved in emotional processing and self- representation are connected to motor control circuits underpinning handwriting production, the strong correlations between personality traits and signature features imply that stable individual differences may influence motor expression [9]. If signature traits do represent personality at all, they do so in a weak and inconsistent manner, according to the small effect sizes and several null findings. This finding is consistent with the more general concept that personality appears probabilistically through a variety of behavioral channels, with each behavioral indication offering only a limited amount of insight into underlying characteristics.

3.4.Limitations

There is limited generalisability to different age groups, educational levels, and cultural contexts because the sample consisted of 117 college students from Bangalore. Selection bias may have been caused by the sampling technique and the limited age range. Measurement error may have been introduced by the subjective judgment used in signature feature coding. The richness of signature traits may not be fully captured by the categorical and ordinal coding method. Despite its strong validation, NEO- FFI is based on self- report and could be influenced by social desirability bias. Causal conclusions cannot be drawn from the correlational design. Unmeasured third variables, such as educational background, cultural standards, or neurological variations, could explain reported relationships.

3.5.Future Considerations

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More advanced techniques for measuring signature attributes should be developed in the future, such as continuous measurement and digital tablets that record dynamic aspects of signature formation as velocity, acceleration, and pressure variation over time (Miguel- Hurtado et al., 2014) [26]. It is crucial to replicate using bigger, more varied samples. Studies that compare signature- personality links between various writing systems throughout cultures may be able to distinguish between associations that are universal and those that are culturally particular. The identification of intricate patterns in signature features is a promising application of machine learning techniques. Future studies should tackle issues like over fitting and model interpretability while combining sophisticated analytical methods with meticulous feature extraction (Ahirwar et al., 2026) [12]. In order to ascertain whether signature qualities offer distinct information beyond other more accessible indications, future research should look at the connections between signature characteristics and other behavioral indicators, such as general handwriting, facial expressions, and vocal characteristics[24].

Conclusion

This study examined the connections between Bangalore college students' handwritten signatures and the Big Five personality traits. The results showed that extraversion and S5 were positively correlated, extraversion and S2 and S9 were negatively correlated, neuroticism and S3 were positively correlated, neuroticism and S6 were negatively correlated, and conscientiousness was negatively correlated with S1. However, neither Openness nor Agreeableness showed any significant correlations, and the general pattern showed low impact sizes among many non- significant interactions. These findings highlight the shortcomings of signature- based personality assessment while contributing to the ongoing empirical investigation of graphological claims. They also partially confirm some proposed correlations. The results are consistent with meta- analytic research indicating that, when they exist, handwriting- personality correlations are weak and may result from variables other than graphological traits in and of themselves. The limitations of the study highlight the necessity of planned replication and careful interpretation. To further our understanding of how personality may be reflected through normal motor behaviors, future research should make use of improved measuring techniques, larger and more varied samples.

In the end, signatures are best viewed as one of many possible behavioral representations of individual characteristics, even though they may contain some information about personality. The weak correlations found in this study imply that signatures should not be utilized as stand- alone personality indicators in practical contexts, but they may support thorough personality assessments when combined with data from other sources.

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