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Review

Survey on handwriting-based personality trait identification

Kinjal Chaudhari*, Ankit Thakkar

Department of Computer Science & Engineering, Institute of Technology, Nirma University, Ahmedabad - 382 481, Gujarat, India

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ABSTRACT

Personality is a combination of various characteristics and qualities of an individual. It may be affected by the growth and evolution of one's values, attributes, relationships with the community, personal memories of life events, habits, and skills. Behaviours and decisions of an individual are largely directed by his/her personality. Identification of such a personality trait can be performed based on an individual's handwriting features. Handwriting may be unique for each person and a person's nature, behaviour, and certain psychological aspects can be inferred based on it. It is introduced as the field of graphology, also called graphoanalysis, to analyze personality based on handwriting. We perceived that many researchers have worked on personality and/or behaviour identification based on handwriting, however, most of them were limited to a few numbers of features. According to graphology, there is a vast range of features of handwriting strokes which carry psychological characteristics of the writer. In this survey, we present links between handwriting and personality psychology and examine different mechanisms for features extraction to predict a writer's personality. Psychologically supported handwriting features help to understand personality traits. The paper relates these features and encourages the use of computer-based graphology for personality prediction. It also discusses applications of graphology in various fields.

1. Introduction

Depending upon the characteristics of an individual, tall or short, fat or slim, dark or fair can be considered as physical traits whereas intelligence, creativity, efficiency are few of the ability traits; social traits may be honesty, richness, talkativeness; another kind of features may be given by the personality traits. These personality traits can be described as "emotional, interpersonal, experiential, attitudinal, and motivational styles" (McCrae & Costa, 2003). Raymond Cattell defined personality as "that which permits a prediction of what a person will do in a given situation" (Cattell, 1950). Cattell predicted behaviour by utilizing traits; he defined personality trait as "that which defines what a person will do when faced with a defined situation" (Cattell, 1979). Identification of personality traits of an individual can be performed based on different aspects such as plain text (Pennebaker & King, 1999), documents (Majumder, Poria, Gelbukh, & Cambria, 2017), handwriting (Kumar, Ravulakollu, & Bhat, 2014), signature (Lokhande & Gawali, 2017), iris position (Ramli & Nordin, 2018), online video games (Feldman, Monteserin, & Amandi, 2017), social media hashtags (Mohammad & Kiritchenko, 2015). This article presents how personality trait can be identified based on handwritten English text; the same with respect to other languages and/or scripts have also been a research interest for many researchers. Devanagari and Latin scripts (Kumar et al., 2014), Farsi (Hashemi, Vaseghi, & Torgheh, 2015; Sharif & Kabir, 2005) as well as Arabic (Al-Sanjary & Sulong, 2017) language-based handwritten texts have been studied, however, we have restricted our survey to only English language.

A neurological brain pattern can be used to represent the personality trait; such patterns build neuromuscular movements (Hashemi et al., 2015). Such movements occur while writing and are the same for every individual who shares the same personality trait. Thus, handwriting is also mentioned as brain writing (Antony & Cap, 2008) and such tiny movements occur unconsciously while writing (Champa & AnandaKumar, 2010a). Thus, we can map these writing movements or strokes with an individual's personality trait. Graphology uses handwriting for the purpose of psychodiagnosis (Downey, 1919). An investigation of physical traits and handwriting patterns can be performed using graphology; it is claimed to be capable of identifying the writer. Handwriting indicates the writer's psychological state at the time of writing; one can also evaluate a writer's personality characteristics (Goldenson, 1984). Identification of an individual's personality is required for various applications such as employment profiling (Coll, Fornés, & Lladós, 2009), psychological analysis like identification of the symptoms of Parkinson's disease (Drotar et al., 2013), medical diagnosis for

* Corresponding author.
E-mail addresses: 17ftphde21@nirmauni.ac.in (K. Chaudhari), ankit.thakkar@nirmauni.ac.in (A. Thakkar).

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detection of heart disease at an early stage (Kedar, Bormane, & Nair, 2016) to name a few.

Graphologists generally analyze an individual's handwriting and/or signature manually. A large number of handwriting samples of certain people is studied; these individuals are found to be having specific characteristics. In these handwriting samples, graphologists look for more frequently appearing traits as compared to that occurring in the general population's handwritten texts (Scanlon & Mauro, 1992). Depending on the expertise of graphologists, they can also identify the writer from a small piece of the handwriting sample. However, this method is slow and prone to errors. To resolve this problem, researchers have worked upon computational graphology which can automatically predict an individual's personality. The study has pointed to the degree of stability; personality is likely to be substantial for individuals over the age of 30 years and it changes little in most people then onwards (Costa & McCrae, 1988; McCrae & Costa, 2003). Also, it has been seen that every individual has a unique handwriting style; a person's nature, behaviour, and certain psychological aspects can be inferred based on the handwriting features. Hence, this brain writing has attracted researchers. Our main objective is to study research work carried out with graphology and provide insights into the personality and behavioural aspects of an individual using their handwritten text. Additionally, we describe personality psychology, trait measurements, and a vast number of handwriting analysis features. We link these features to personality characteristics, explain previous research works to identify them using computational graphology and discuss their outcomes. We present a list of applications where handwriting-based personality traits have been used. As compared to the previously conducted surveys (Garoot, Safar, & Suen, 2017; Kamboj & Bajaj, 2015; Kedar & Bormane, 2015; Kedar, Bormane, Dhadwal, Alone, & Agarwal, 2015a; Kedar, Nair, & Kulkarni, 2015b), we provide exhaustive features of handwriting that can be used for the personality detection. In addition to that, we have also provided links between handwriting features and potential personality traits in this paper. We conclude our work with the identified challenges in the given field. We believe this article will bring cognizance to the concept of graphology and procedures to achieve the best suitable solutions.

This article is organized as follows: Section 2 depicts the psychology of personality with various types of personality traits. Section 3 presents broad discussions on the handwriting analysis. Section 4 is a survey on computerized graphology-based research and an overview of datasets; Section 5 describes applications of handwriting analysis in various fields. We discuss highlights of the paper and summarize our literature survey in Section 6. The concluding remarks on our survey with major challenges in existing research are given in Section 7.

2. Personality psychology

In certain respects, the quotation that "every man is like all other men" (Kluckhohn, Murray, & Schneider, 1953) is concerned with the general psychology. In contrast to that, the phrase that "every man is like some other men or like no other man in certain respects" (Kluckhohn et al., 1953) is concerned with the personality psychology (Allport, 1937). Dispositions are non-permanently stable behavioural tendencies; concerned personality psychology of individuals of a similar age differs from one another (Corr & Matthews, 2009). Personality dispositions (Allport, 1937), or personality traits (Funder, 1991) characterize the personality of an individual.

There have been different theories for particular characteristics of personality. These theories have often lead to the development of various trait measures. Many scales have been created. For example, Rokeach developed a questionnaire to measure the concept of dogmatism (Rokeach, 1960), Crandall proposed a trait preference list to assess the concept of social interest (Crandall, 1980). With respect to Jung's theory of psychological types, Introversion and Extraversion attitudes were used (Jung, 1923) and it was further upgraded to Neuroticism and Psychoticism dimensions (Jung, 2016). The Myers–Briggs Type Indicator (MBTI) (Myers, McCaulley, Quenk, & Hammer, 1998) was developed based on Jungian psychology.

In English, Allport and Odbert initially found 18,000 trait-descriptive terms out of which 4000 terms were identified that clearly referred to personality traits (Allport & Odbert, 1936). Cattell grouped the synonyms and considered 35 cluster scales; they factored and 12 dimensions were identified with additional four dimensions. Hence, it became the Sixteen Personality Factor Questionnaire (16PF) (Cattell & Mead, 2008). There were further modifications to Cattell's 35 rating scales (Tupes & Christal, 1992), reducing them to five (Norman, 1963). Goldberg formed his own sets of synonyms and replicated the Five-Factor Model (FFM) (Goldberg, 1990; 1993). On the other hand, Costa and McCrae matched their factors to Norman's scale (Norman, 1963); they nested the three-factor model within FFM and named it as the NEO Personality Inventory (NEO-PI) which is suitable for studying ageing and personality (Costa & McCrae, 1985). They also developed the Revised NEO-PI (NEO-PI-R) (Costa & McCrae, 2008).

These are different measures of personality traits which can be used based on the application. However, measuring personality requires techniques for collecting and processing data. Traits endure over time for each individual according to which one's personality can be characterized (Granatyr et al., 2017; McCrae & Costa, 2003). This expects a range or distribution of scores as the result of trait measure. Such scores can be achieved by self-reports, peer ratings, or observer ratings. An individual's personality trait can be measured using one of the most commonly used techniques shown in Fig. 1 (Cattell & Mead, 2008; Goldberg, 1993; Myers et al., 1998).

3. Handwriting analysis

Graphologists manually look for analytic outcomes while identifying personality or behavioural traits of an individual from his/her handwriting; two methods are the French approach, also known as the atomistic method and the German approach, also called the holistic approach (Ow et al., 2005). The French approach is an isolated trait method as it breaks down the handwriting sample into components for examining them individually. On the other hand, the German approach, or the gestalt approach, determines behaviour using handwriting as a whole (Ow et al., 2005). It provides an intuitive apprehension of the overall writing and can evade segmentation ambiguity and shape variability issues of the characters (Madhvanath & Govindaraju, 2001; Ow et al., 2005). Graphologists may consider a combination of both methods (Lowe, 1999). These factors work as features for computational graphology. This section provides a detailed study on the psychological meaning of a particular handwriting feature and its variants. The outcomes of such analysis can be mapped with respective personality trait model.

3.1. Zone

It is the vertical dimension of the writing movement. In the time sequence, the three zones of writing, upper, middle, and lower zones represent the future, present, and past, respectively. Ego development in an individual may be due to one's intellectual and spiritual sphere, social self on the daily basis, and the unconscious instinctual drive. The proportion of three zones decides the balance between these major areas of ego development (Amend & Ruiz, 1980). Various features of the zone of writing and associated personality characteristics are given in Fig. 2 (Amend & Ruiz, 1980).

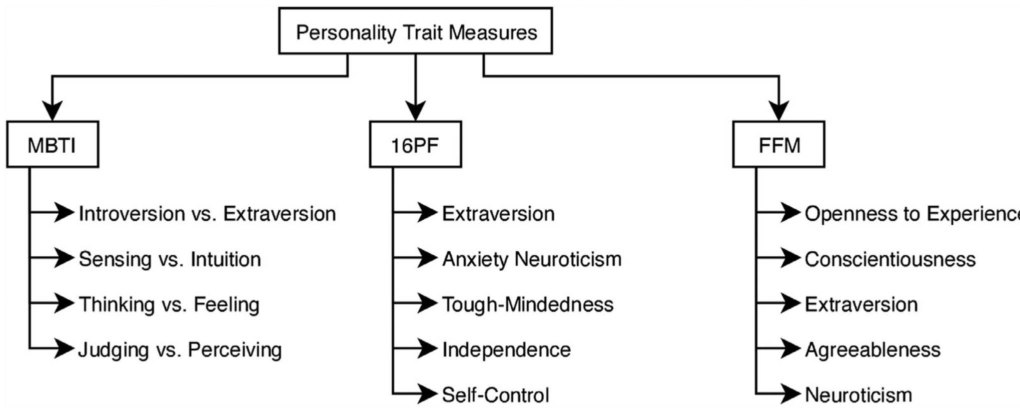

Fig. 1. Various personality trait measures (Cattell & Mead, 2008; Goldberg, 1993; Myers et al., 1998).

Fig. 2. Zone features and associated personality characteristics.

The upper zone (UZ) contains intellect, imagination, mental perceptions, spiritual aspiration, and articulation of moral attitudes of the writer. A writer demonstrates the extent and quality of his self-consciousness in UZ. The middle zone (MZ) represents ego or self-conscious, social self, emotional expression, daily life, and goal-oriented part of the personality of the writer. The lower zone (LZ) expresses an instinctual self, sensual perception, basic as well as unconscious drives for security, and the organic needs of the writer. UZ, MZ, and LZ embody fantasy, immediacy, and memory, respectively. The English letters, ‘b’, ‘d’, ‘h’, ‘k’, ‘l’ are examples of UZ letters; ‘a’, ‘c’, ‘e’, ‘i’, ‘m’ are examples of MZ letters; ‘g’, ‘j’, ‘p’, ‘q’, ‘y’ are examples of LZ letters. Only the letter ‘f’ can be found in all three zones (Amend & Ruiz, 1980). However, there are specific characteristics of each of these zones.

3.2. Baseline

It forms an invisible line within the zones. An individual’s personality towards handling the combined influences from various drives can be expressed by level or steadiness characteristics of the baseline. It can be thought of as the ego-adjustment line (Amend & Ruiz, 1980); baseline features and personality-based associated characteristics are shown in Fig. 3 (Amend & Ruiz, 1980).

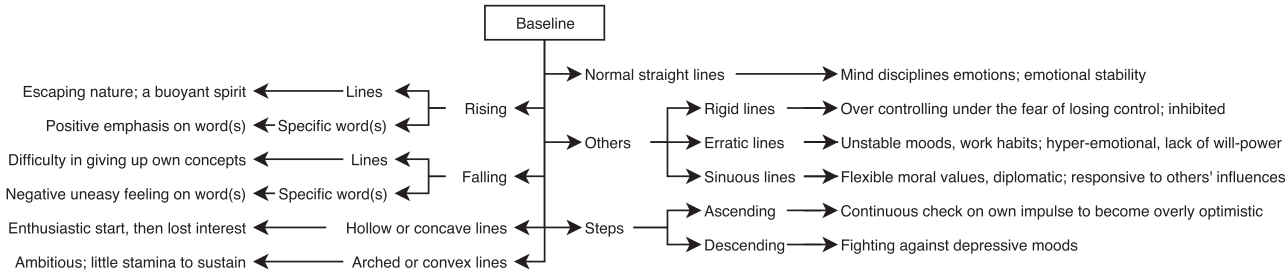

Fig. 3. Baseline features and associated personality characteristics.

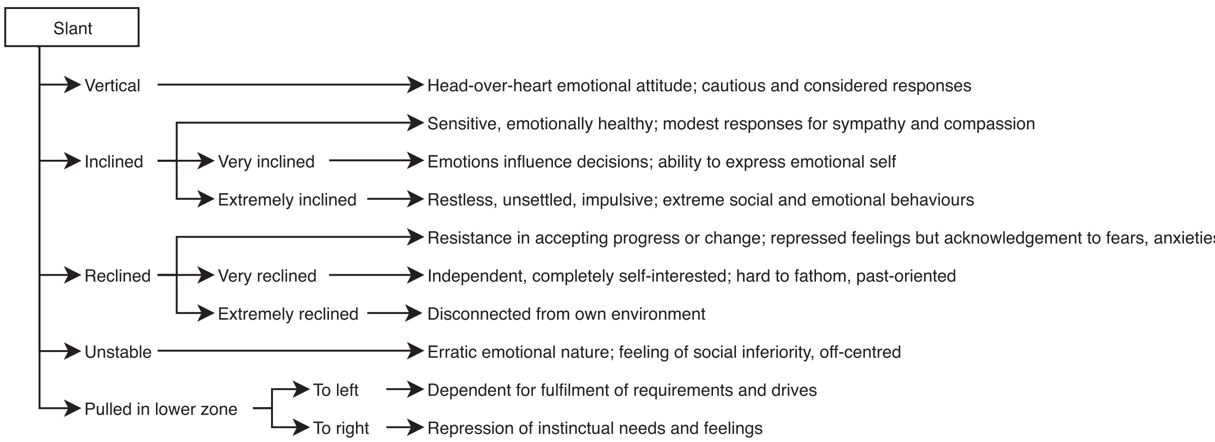

Fig. 4. Slant features and associated personality characteristics.

3.3. Slant

It is the horizontal dimension of the writing movement which measures social alignment (Amend & Ruiz, 1980). Zonal dimensions reveal perception, analysis, thought and individual character of a writer, whereas slant dimensions reveal emotion, relationship, communication and social personality of the writer. An angle formed between the downstroke of the letters and the baseline represents the direction of letter slope; it is the slant of writing. It has three main types: reclined, vertical, and inclined; these features can be associated with specific personality characteristics as shown in Fig. 4 (Amend & Ruiz, 1980).

3.4. Pressure

Height, width, and depth are considered to be three dimensions of the handwriting. Here, depth dimension can be noticed when pressure is applied against the writing surface with shading. It can be associated with resultant stroke width, pastiosity or sharpness of the inking pattern (Amend & Ruiz, 1980). The force while writing indicates the degree of available energy. The writing contains upstrokes and downstrokes which can be considered as release strokes and contracting strokes, respectively.

Other aspects of pressure are also considered in handwriting analysis. One of them is stroke width, thin or thick, which displays energy in action (Amend & Ruiz, 1980). It is dependent on the manner in which the writer grasps the pen. Another aspect is pastiosity which means an extra flow of ink from the pen on the paper. Sharpness is another aspect which indicates clean writing strokes. An individual's sensuality or spirituality may be found by examining the inking patterns. Fig. 5 (Amend & Ruiz, 1980) indicates pressure and its related features associated with personality characteristics.

3.5. Size

It is a measurement of the importance that the writer gives to himself and his own actions. In other words, size represents the writer's characteristics towards inspiring himself upon his surroundings. The standard height of middle zone letters is 3 mm or 1/8th of an inch (Amend & Ruiz, 1980). Personality characteristics associated with various size attributes are shown in Fig. 6 (Amend & Ruiz, 1980).

3.6. Spacing

Each written letter can represent the characteristics of the writer. The spacing or the distance between letters indicates how the writer relates to other people on a personal level. On the other hand, the spacing between words represents the writer's need for emotional comfort with others and the distance he would like to maintain between himself and the society. However, the spacing between lines on the page refers to the clarity and orderliness of the writer's philosophy and reasoning. It provides clues about the extent to which he wishes to interact with people in his surroundings; Fig. 7 (Amend & Ruiz, 1980) depicts personality characteristics associated with the features of spacing.

3.7. Speed

The speed of writing represents the tempo of the writer's line of thought, gestures, actions, and reactions. Observations show that curves are easier to write than straight or broken lines and angles; it is difficult to draw dots at high speed and they may turn into symbols such as commas or dashes (Amend & Ruiz, 1980).

The strokes are found to be controlled, hesitant, unsteady, or even retouched when the text is written slowly. In such a case, very small or significantly huge letters in size are likely to have

Fig. 5. Pressure features and associated personality characteristics.

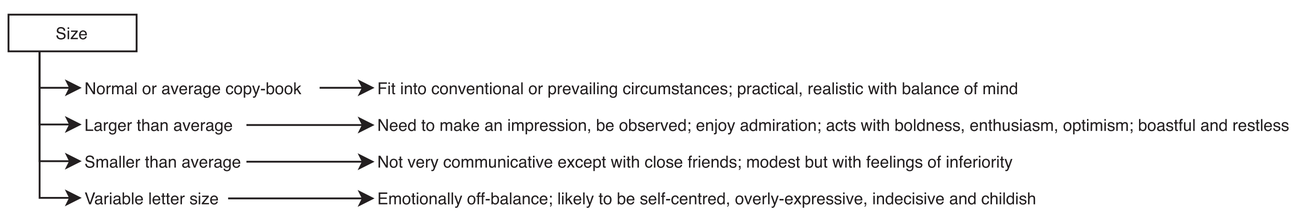

Fig. 6. Size features and associated personality characteristics.

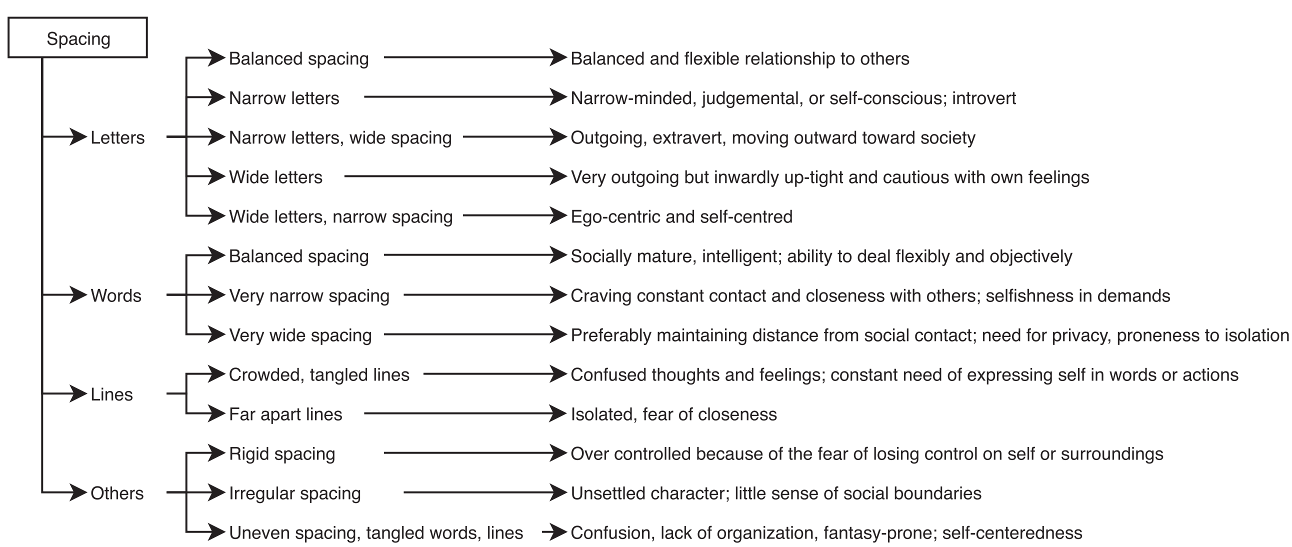

Fig. 7. Spacing features and associated personality characteristics.

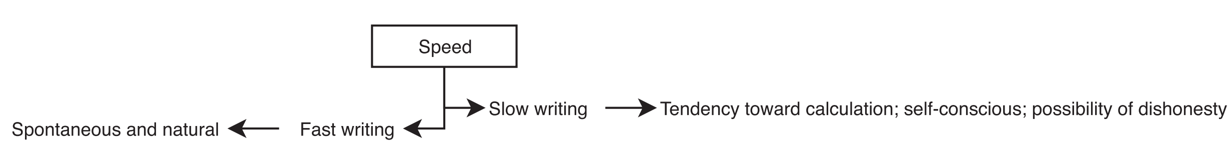

Fig. 8. Speed features and associated personality characteristics.

shrunken or stretched out shapes. The rhythm and form level are poor overall. On the other hand, faster writing-speed would have animated and rhythmic patterns with smooth, unbroken strokes. The directional trend is found to be rightward with letters streamlined and of medium size. These are referred for associated personality characteristics as in Fig. 8 (Amend & Ruiz, 1980).

3.8. Stroke

In writing strokes, basic two kinds of graphical movements are traced. They are curved movement and straight movement. A circle is considered to be the ideal curved shape; in handwriting, other formations of circle are ovals and loops (Amend & Ruiz, 1980). A

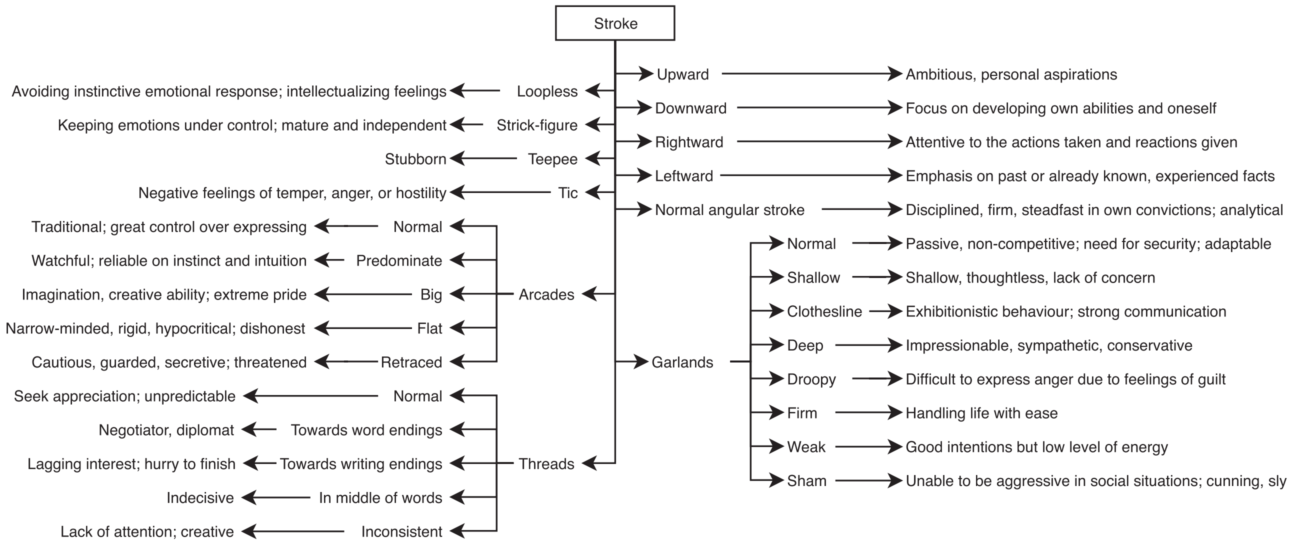

Fig. 9. Stroke features and associated personality characteristics.

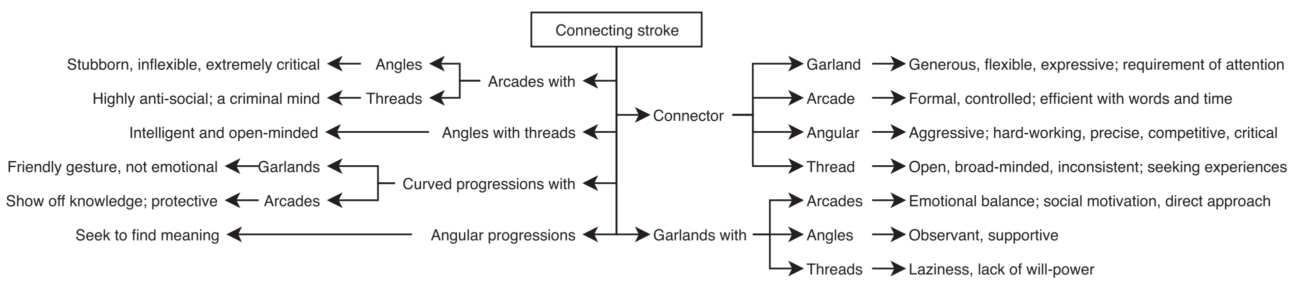

Fig. 10. Connecting stroke features and associated personality characteristics.

circle is considered to be the unification of the female and male forces that are expressed by the yin/yang principle (Fang, 2012).

The other stroke movement is straight in graphical nature which may result in vertical, horizontal or diagonal strokes, or in the shapes of square, cross, triangle or the English letter ‘X’. According to Amend and Ruiz (1980), straight line and angular shape symbolize human aspiration and the abstract mind; the physical world may be given by circular shapes whereas straight strokes and shapes are associated with the mental world which convey authority, ambition, and power. It has been observed that the angular formations are slower to write than that of the circular formations.

Various stroke features and associated personality characteristics are given in Fig. 9 (Amend & Ruiz, 1980); these stroke movements have major formations like garland, arcade, angular and thread. The lower and upper arcs of a circle depict garland and arcade strokes. The concave shape of a garland formation indicates an open, receptive and responsive writer. On the other hand, the convex shape of an arcade formation represents a secretive, guarded, protective, resistant and proud writer. Threaded movement can be considered to have straight and curved strokes combined, however, the quality of a line is generally formless. It represents evasion from commitment, control, and direction.

3.8.1. Connecting stroke

It is the link between letters which provide traces to the social attitudes and intellectual abilities of a writer; these personality characteristics associated with the connecting stroke features are shown in Fig. 10 (Amend & Ruiz, 1980); most of the writings may contain more than a single type of connecting strokes.

3.8.2. Connectedness

Connecting letters form a word which psychologically represents the maturity and speech fluency. The degree of connectedness indicates the writer’s line of thought, intellectual abilities, and attitudes towards community (Amend & Ruiz, 1980); these personality characteristics associated with connectedness features are demonstrated in Fig. 11 (Amend & Ruiz, 1980).

3.8.3. Ending stroke

It is the stroke at the end of a word. An ending stroke, also known as a terminal stroke, is helpful in giving clues to how a writer may get involved with his targets and other people. Fig. 12 (Amend & Ruiz, 1980) refers to the personality characteristics associated with the ending strokes.

3.9. Margin

A writer’s perspective towards the world can be identified based on how he fills the page with a handwritten script. The English script is normally written on the left to right horizontal manner; a writer generally initiates writing from the left side of the paper which portrays the past, whereas the right side symbolizes his/her future objectives. The way a handwritten script is arranged on a page may represent a quality of the writer’s etiquette, socio-cultural propensity, leaning towards art, or absence of these (Amend & Ruiz, 1980); margin features and associated personality characteristics are as given by Fig. 13 (Amend & Ruiz, 1980).

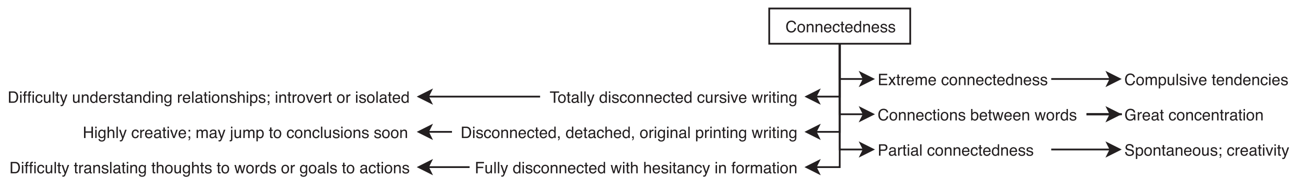

Fig. 11. Connectedness features and associated personality characteristics.

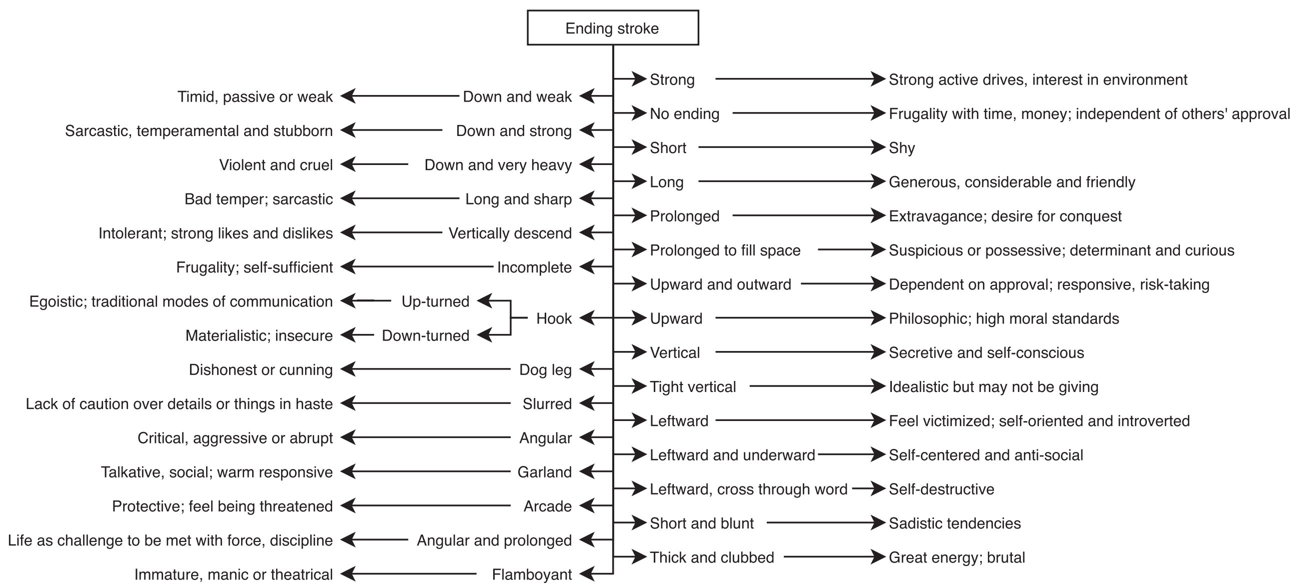

Fig. 12. Ending stroke features and associated personality characteristics.

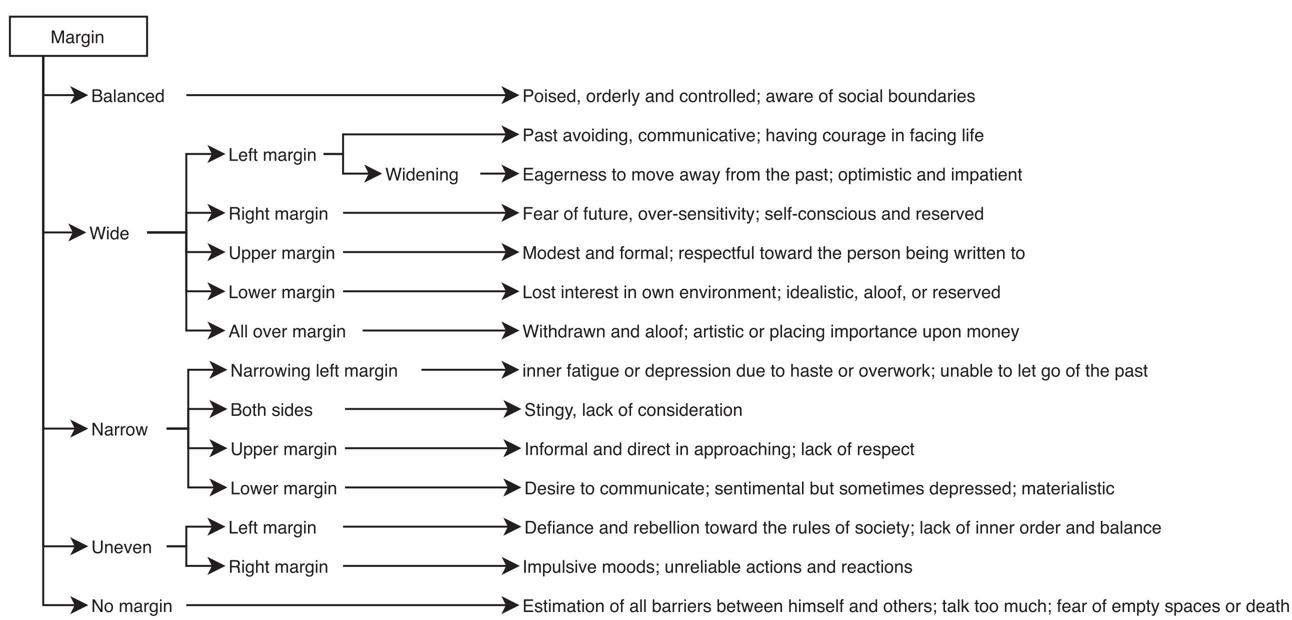

Fig. 13. Margin features and associated personality characteristics.

3.10. Shape

The circular strokes can be seen in loops and oval shapes of letters. Loops represent emphasis put on emotions while ovals convey emotions on a vocal and social level. On the other hand, the angular strokes have various shapes like square, cross, triangle and the English letter ‘X’ which have distinct meanings as symbols (Amend & Ruiz, 1980). These shapes and their association with personality characteristics are given in Fig. 14 (Amend & Ruiz, 1980).

3.11. English letters

Some of the English letters indicate specific characteristics such as social attitudes, clarity of thoughts, habits, and/or abilities. The capital and small letters also hold precise meanings in graphology.

3.11.1. English letter: ‘d’

This letter reveals the self-importance and the social viewpoints of the writer. The letter ‘d’ can notify about the writer’s social

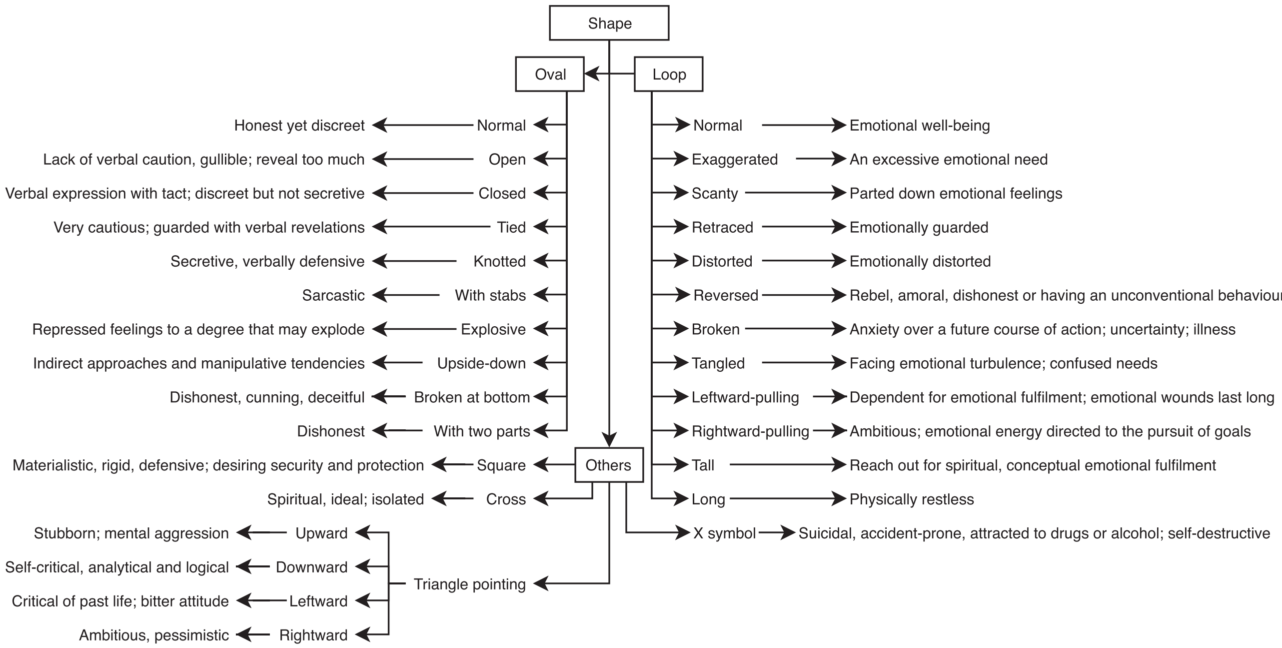

Fig. 14. Shape features and associated personality characteristics.

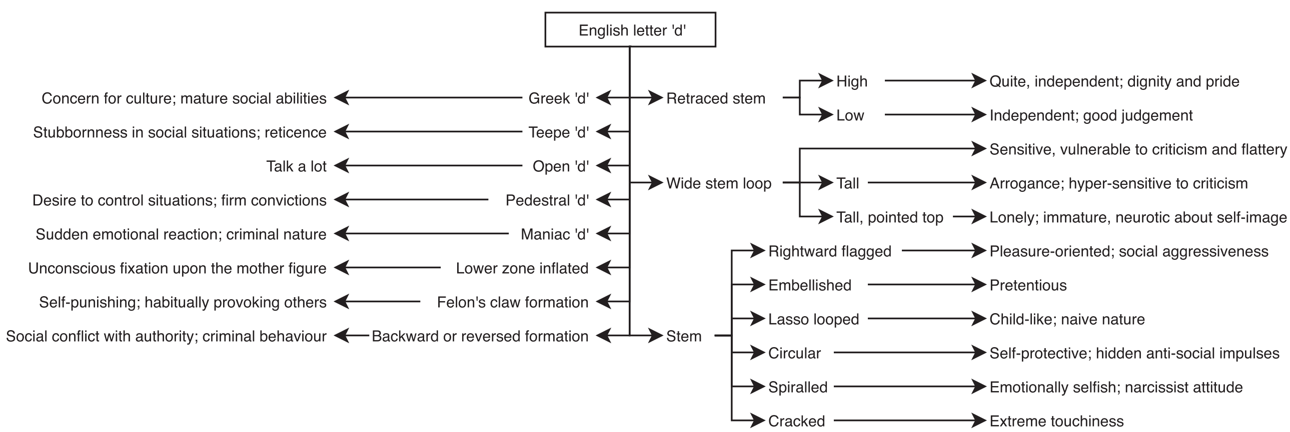

Fig. 15. Features of English letter 'd' and associated personality characteristics.

interactions with other people (Amend & Ruiz, 1980); associated personality characteristics with the features of letter 'd' are shown in Fig. 15 (Amend & Ruiz, 1980).

3.11.2. Personal pronoun: 'I'

Writer's flexibility, ego, and dependency can be disclosed by examining a single English letter 'I' and its formations. The mother and the father figures have certain influences on the development of an individual child's personality; the quality and extent of such influences can also be indicated with this letter (Amend & Ruiz, 1980). Fig. 16 (Amend & Ruiz, 1980) indicates personality characteristics associated with the features of the personal pronoun 'I'.

3.11.3. English letter: 'i'

The dot of the English letter 'i' is considered important in graphology. While having forward movement in handwriting, placing a dot, specifically over the stem of letters such as 'i', may be considered as an interrupt. It can be clearly seen that only a few slow, careful hands place it exactly over the stem of the letter 'i' in a precisely round shape. This i-dot relates to the intellect and aspirations. It may reveal enthusiasm and practicality (Amend & Ruiz, 1980). Specifications of personality characteristics associated with the features of the English letter 'i' are given in Fig. 17 (Amend & Ruiz, 1980).

3.11.4. English letter: 't'

The t-bar is considered to be one of the most graphologically important letters of the English alphabets. The t-bar is a separate and distinct line which is produced when the writer interrupts the normal hand movements while writing. Various parameters and attributes of the t-bar reveal the rhythm and impact of the writer's willpower and his personal drives (Amend & Ruiz, 1980). These features and associated personality characteristics are shown in Fig. 18 (Amend & Ruiz, 1980).

3.11.5. English letter: 'y'

This letter indicates the writer's sexual interests, habits, and abilities. Its formations in lower zone give information about attitudes towards materialism and security. It is also a source of energy and creativity (Amend & Ruiz, 1980). Features of the English letter 'y' and associated personality characteristics are shown in Fig. 19 (Amend & Ruiz, 1980).

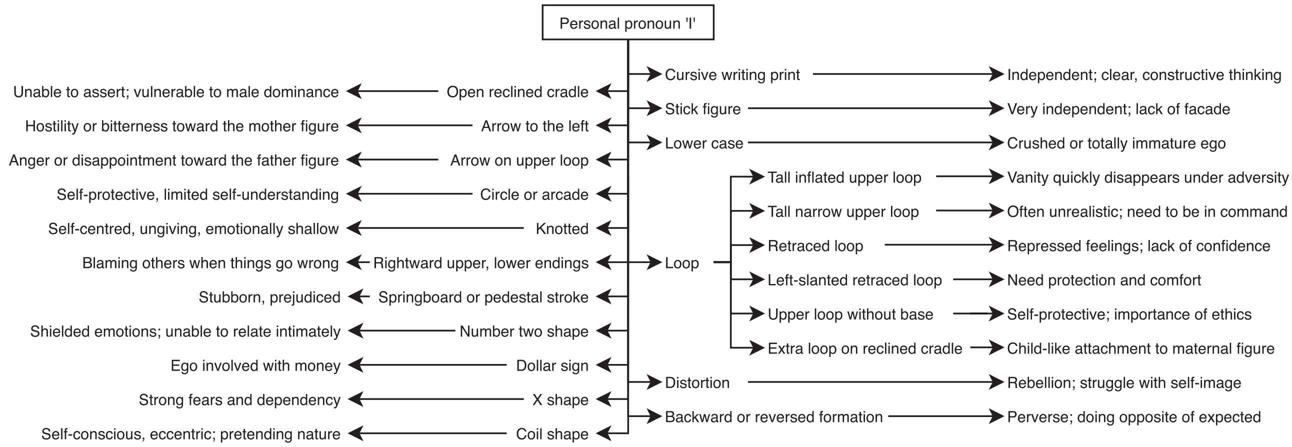

Fig. 16. Features of the personal pronoun 'I' and associated personality characteristics.

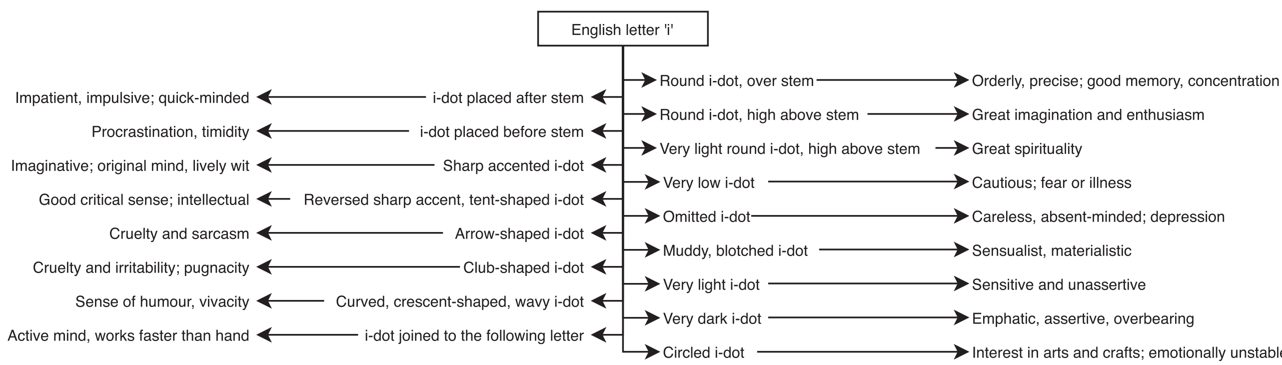

Fig. 17. Features of English letter 'i' and associated personality characteristics.

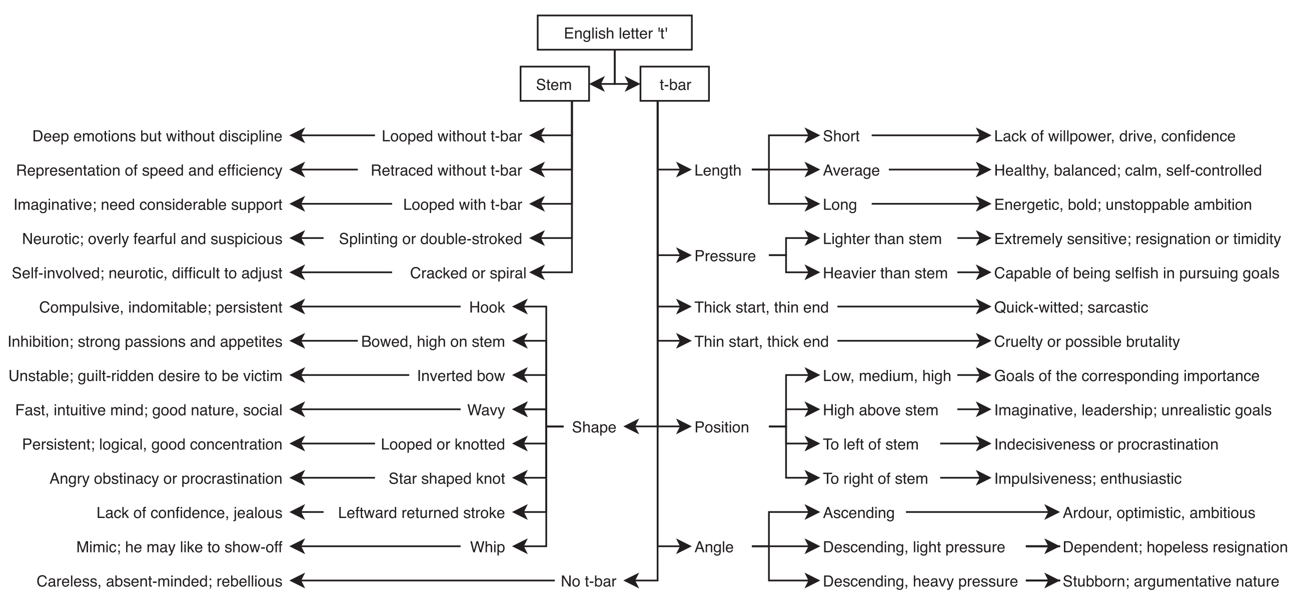

Fig. 18. Features of English letter 't' and associated personality characteristics.

3.11.6. Capital english letters

The English language has both, capital and small letters. Here, the capital letters represent the public side of the writer. Also, they reveal unconscious inner attitudes. The capital letters can be evaluated based on the size, the form, and the inherent originality and grace (Amend & Ruiz, 1980); these features and associated personality characteristics are shown in Fig. 20 (Amend & Ruiz, 1980).

3.11.7. Small english letters

The English small letters provide various tangents about the writer's culture, inclinations, etc. These letter-specific inclinations are to be evaluated when they appear as a spontaneous writing characteristic and not as a misplaced stroke (Amend & Ruiz, 1980); Fig. 21 (Amend & Ruiz, 1980) depicts features of small English letters and associated personality characteristics.

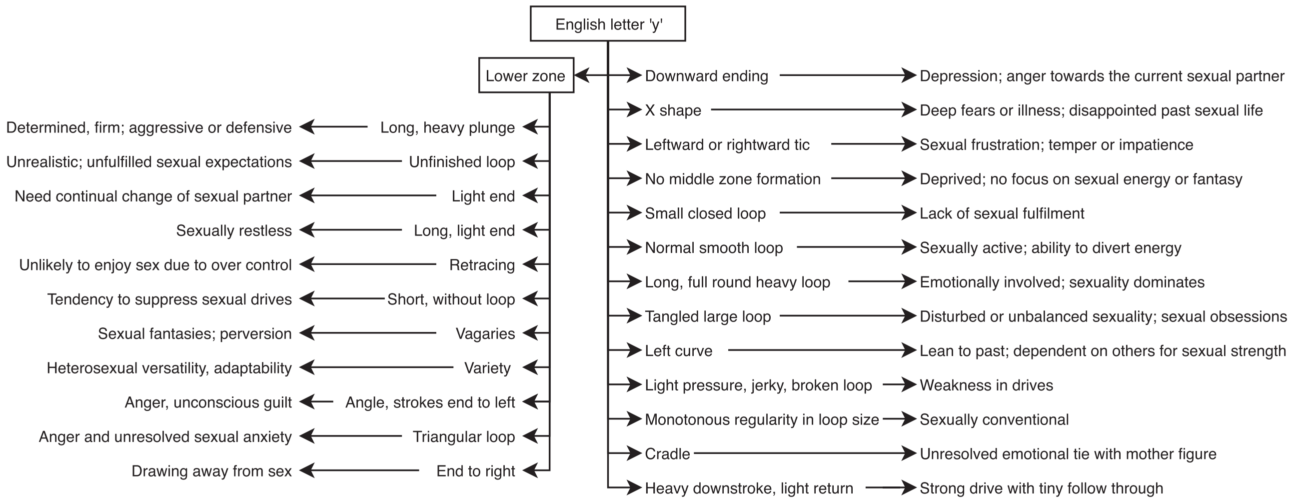

Fig. 19. Features of English letter ‘y’ and associated personality characteristics.

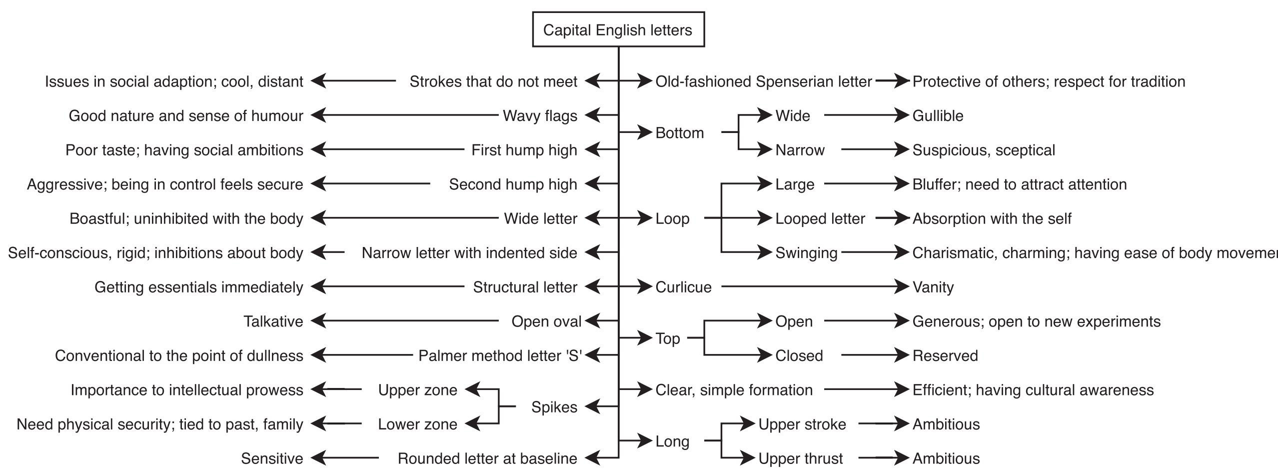

Fig. 20. Features of capital English letters and associated personality characteristics.

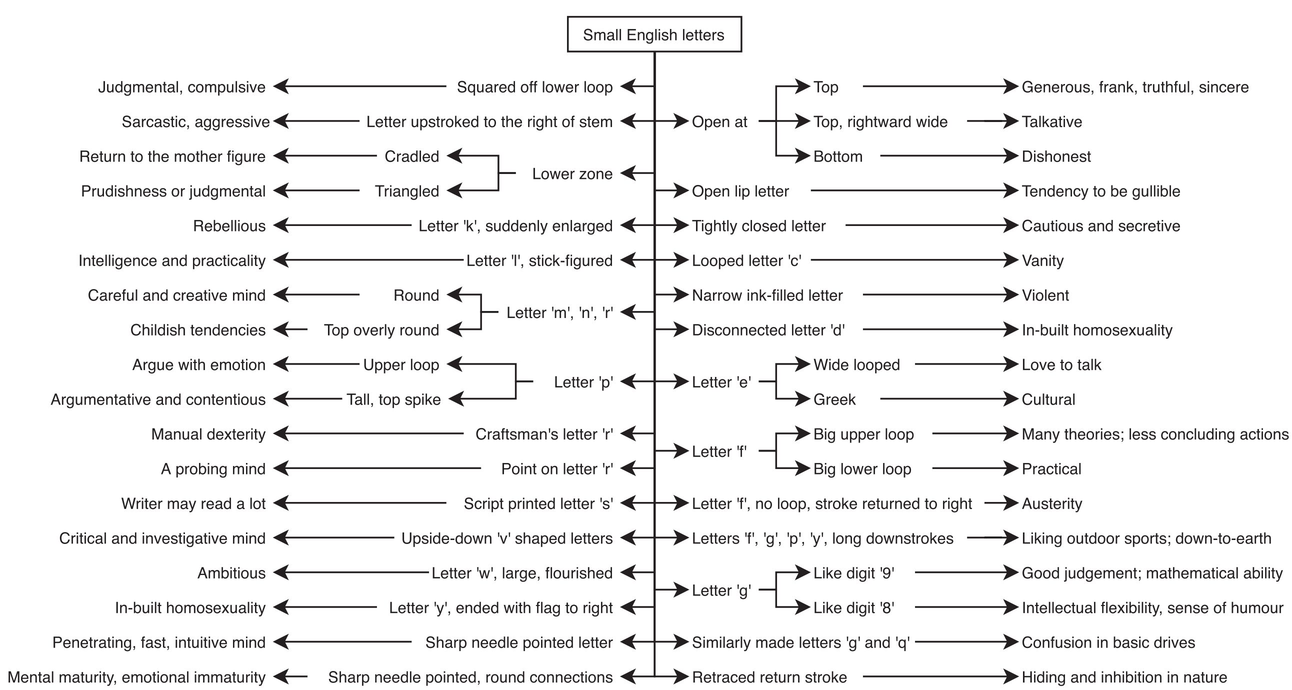

Fig. 21. Features of small English letters and associated personality characteristics.

3.12. Other scripts

Apart from English, various other languages and/or scripts have been explored by researchers to identify handwriting-based personality. These scripts include Chinese, Devanagari, Persian (Farsi), Arabic to name a few. Though we have restricted our survey to English handwriting-based personality traits, insights of various scripts may be helpful to interested researchers. It must be noted that writer identification is significantly different from a writer's personality identification; individual research has been carried out on both these fields.

The Chinese characters are different from the English characters; they do not constitute an alphabet. Chinese writing system is considered to be logosyllabic where no direct information on phonetic segments is provided (Peng & Wang, 2011; Wang, 1973). Instead of the letter-to-phoneme correspondences of the alphabetic writing system such as English, Chinese correspondences are character-to-syllable (Shu, Chen, Anderson, Wu, & Xuan, 2003). In Chinese writing system, each character is written using two types of unit: the stroke and the radical (Wang, 1973). The order and the geometric position of the strokes are important and hence, Chinese characters with similar characteristics may have different meanings (Leng & Shamsuddin, 2010). Authors also mentioned in Leng and Shamsuddin (2010) that no explicit separator is used in Chinese sentences; the words are written continuously with an equal space between them. In Wang et al. (2009), authors extracted character spacing feature for identifying its correlation with writer's personality characteristics such as reasoning and sensitivity.

Devanagari script has forty-seven primary characters out of which, fourteen are vowels and thirty-three are consonants (Cardona & Jain, 2007); the text is written as a group of words. It can be recognized by a horizontal line, called Sirorekha, generally connecting the top of individual characters of a word. Such bridging line is useful for estimating the baseline alignment. In Kumar et al. (2014), authors collected and compiled dataset, CPAR-2012 (Kumar, Kumar, & Ahmed, 2013; Kumar & Ravulakollu, 2014a; 2014b). They extracted slant, baseline direction, letter size, and arrangement features and represented in the form of fuzzy subsets; they considered margins, inter-line spacing, inter-word spacing, and intra-word spacing as a part of arrangement feature. They achieved 88–97% accuracy on the test set. Authors pointed out that the entire text might be disoriented in terms of Sirorekha, which might influence the overall estimation of the writer's mood (Kumar et al., 2014).

Persian language, also commonly known as Farsi, is written and read right to left. It has six vowels and twenty-three consonants. The earliest approach for computer-aided graphology for Farsi handwritten text was proposed in Sharif and Kabir (2005). Authors considered some of the predominant handwriting features such as right and left margins, word expansion, letter size, line spacing, word spacing, line skew, word slant, and ratio of vertical to horizontal elongation. They worked with 142 handwriting samples; results of correct classification for each of these features were shown (Sharif & Kabir, 2005). A similar set of features were considered for Farsi language in Hashemi et al. (2015) where writer's personality was classified using support vector machine (SVM).

Modern Standard Arabic consists of a total of twenty-eight consonants out of which six letters are vowels as well; it also has two diphthongs. Arabic script is written and read from right to left and it does not have capitalization aspect as that in English (Alkahtani, Liu, & Teahan, 2015). Identification of personality from Arabic handwritten script is a challenging task and limited research has been carried out on the same. In Al-Sanjary and Sulong (2017), handwriting features such as intensity, line spacing, height of words and characters, baseline, slant, and word spacing were extracted. The classification was performed using clustering technique on the standard KHATT dataset (Mahmoud et al., 2014) of Arabic handwritten text. Authors concluded that centroid and single cluster methods exhibited stable performance when the number of clusters was increased (Al-Sanjary & Sulong, 2017). However, a majority of the extracted features seem to be general and are not specifically associated with Arabic language.

Other scripts have also been explored for handwritten character recognition, writer identification, and personality characterization; interested researchers may consider multilingualism approaches for the same.

4. Computerized graphology

Many researchers have considered various attributes for identifying personality traits based on handwriting. Different handwriting features are considered to understand human behaviour. They are also applied to various applications such as medical diagnosis, career guidance, emotion identification to name a few. In this section, we have briefly explained the research work carried out to identify personality using computational graphology. We have reviewed the methodology used and result outcomes.

4.1. Behaviour-based personality identification

An individual's behaviour is the reflection of his/her personality. Changes or fluctuations in behaviour or emotions may be seen while examining one's handwriting. Such changes in moods can be encountered from an individual's handwriting as well. Identification of such behavioural traits are possible using graphology.

One of the earliest work defined for computer-aided graphology (CAG) included scanning, pre-processing, feature extraction and feature analysis steps (Sheikholeslami, Srihari, & Govindaraju, 1995). Authors removed digitization artifacts, applied thresholding and removed guidelines in the pre-processing step. They extracted features such as left, right, and bottom page margins, line spacing, line direction, slant, and ratios of the upper, middle, and lower zones. They implemented context-free grammar with 50 rules for analyzing these features and mapped them with interpretations using syntactic pattern recognition. CAG system was tested on 25 handwritten samples and personality descriptions of the writers were given as the output which was consistent with graphologists' interpretation (Sheikholeslami et al., 1995).

Based on two of the classical methodologies, crisp and fuzzy, an offline handwriting analysis approach was proposed (Mogharreban, Rahimi, & Sabharwal, 2004). Authors considered the rule-base where inputs were baseline and slant angle features. They identified rules explaining 15 personality traits that could be given as an output of the system.

For analyzing an individual's personality, a single feature or a combination of various features can be used. To identify the level of ambition, authors analyzed the lower letter 't' from the handwriting samples (Mutalib, Abdul Rahman, Yusoff, & Mohamed, 2007). They collected handwriting samples from 50 respondents using questionnaires and by asking them to write one sentence. They pre-processed the scanned images using digitization, normalization, scaling, noise removal, binarization, and segmentation. Recognition of letter 't' and the level of ambition was performed using artificial neural networks (ANNs). Based on the t-bar, the level of ambition was identified using ANN. They considered three types of t-bar: up-turned, straight, and down-turned and defined ambitions to be optimistic, controlled (or balanced), and pessimistic, respectively. The average accuracies for recognizing letter 't' and ambition were 90.27% and 60%, respectively (Mutalib et al., 2007).

Authors presented three kinds of measurements of handwriting features: general for overall impression, fundamental for primary classification of patterns, and accessories for graphical symbols (Ahmed & Mathkour, 2008). Handwriting features namely slant, baseline, speed of writing, letter size, continuity, form, arrangement, and pressure were extracted and applied using a rule-based system. Authors experimented with handwritten samples of 35 students for personality trait prediction.

Another way to predict personality is the rule-based approach. Using two features, baseline (ascending, descending, level) and pen pressure (light, medium, heavy), authors introduced rule-base for their experiment and developed a set of nine (if-then) rules for decision-making (Champa & AnandaKumar, 2009). They used polygonalization and thresholding techniques to identify baseline and pen pressure features. They introduced nine respective personality traits, majorly focusing on one's emotional intensity and positive attitude.

For predicting personality using a computer, Champa and AnandaKumar (2010a) proposed a methodology for behavioural analysis without human intervention. They considered three features: baseline, pen pressure, and height of t-bar on the stem of the letter 't'. The scanned handwritten documents were applied with polygonalization method for calculating the baseline slant; the foreground pixels in the thresholded image were used for calculating the pen pressure (Srihari, Cha, & Lee, 2001). Using a template matching method, the t-bar height on the stem of the letter 't' was performed (Champa & AnandaKumar, 2008). Champa and AnandaKumar (2010a) used five predefined templates for the letter 't' in a 6×5 grid. From the scanned image, only the letter 't' was selected and resized to the grid size of the templates. Hamming distance (Tian & Shen, 2005) was found between the input image and the templates to make a match of the pattern. Hence, the extracted features with three different values of the baseline slant (ascending, descending, level), two different values of the pen pressure (light, dark), and five different patterns of letter 't' were given as the inputs to ANN; the outputs were given from 30 different personalities. Using the backpropagation technique, performance goal of 0.099 was achieved in the shortest time when the number of hidden layer nodes was 8 and the number of epochs was set to 4500 (Champa & AnandaKumar, 2010a).

Champa and AnandaKumar (2010a) extended their work by including two more features: lower loop of letter 'y' and slant of writing (Champa & AnandaKumar, 2010b); using the generalized Hough transform (GHT), they calculated the shape of the lower loop of 'y' and the slant of writing was evaluated using template matching with hamming distance. They considered three values of baseline, two values of pen pressure, five positions for 't', ten shapes of the lower loop of letter 'y', and five values of writing slant, which were taken as inputs to the rule-base (Champa & AnandaKumar, 2010b). They used a database of 120 handwritten samples from 120 writers. They evaluated personality prediction manually as well as computationally and compared the efficiencies for each feature.

For predicting the nature of the write, segmentation-based handwriting analysis was proposed (Prasad, Singh, & Sapre, 2010). Here, handwriting analysis can be considered as a projection technique; handwriting is one of the ways of a person's transactions with stress. With 100 writers, each writing a 70–80 words document in running hand had been collected and scanned. After performing noise removal, orientation correction, smoothing, opening, and segmentation into lines, words, and letters, dimensionality reduction provided feature vectors (Prasad et al., 2010). The features included size of letters, slant of words and letters, baseline, pen pressure, spacing between letters and words. They used SVM classifier with radial basis function (RBF) kernel to classify handwriting styles and the writer's corresponding psychological personality traits. Prasad et al. (2010) achieved 93.86% accuracy with RBF kernel as compared to others.

As a part of processing in computation graphology, the previously undertaken techniques mainly included polygonalization, GHT, segmentation, and template matching. These techniques were claimed not to be very simple for automation (Kamath, Ramaswamy, Karanth, Desai, & Kulkarni, 2011); authors believed that there was a need for developing simple methods to automate. They developed an automated handwriting analysis system (AHWAS) where they cropped the scanned image of a handwriting sample, applied RGB (Red Green Blue) threshold and segregated the region of interest (RoI). They considered eight features: size of letters, baseline, pen pressure, slant, breaks, spacing between words, margins, and speed of writing. They took 100 words of written text from 30 people within the age group of 20 – 24 years. They applied image processing and compared their outcomes with inferences made after the manual analysis. The comparison result was found to be more than 80% (Kamath et al., 2011).

Researchers have experimented with different handwriting features to predict attitudes, qualities, sentiments or behavioural facts of an individual. Based on the target output, various combinations of these features have been used. In Grewal and Prashar (2012), authors applied the pre-processing steps including polygonalization, thresholding, and template matching for extracting three different values of the baseline (rising upwards, straight, slanting downwards), five different values of the letter slant (vertical, moderate right, extreme right, moderate left, extreme left), two different values of the pen pressure (heavy, light), five different formations of letter 'f' and six different formations of letter 'i' (Grewal & Prashar, 2012). They carried out this training experiment with handwritings collected from 50 persons. They used ANN which provided the corresponding personality traits and calculated mean squared error (MSE) to show regression line of the outcomes; MSE reduced with an increase in the number of epochs.

Another approach, handwriting analysis-based individualistic traits (HABIT) prediction, was developed to predict personal behaviour of an individual (Rahiman, Varghese, & Kumar, 2013). This system demanded human intervention for choosing RoI. After preprocessing, resizing, and cropping the image into lines, words, and characters, the data points were plotted by the user as the points of interest. Authors considered features such as pen pressure, slant of letters, baseline, size of letters, and spacing between words (Rahiman et al., 2013). They used least square linear regression method for trait identification; the human decision process guided the system to achieve higher accuracy (Rahiman et al., 2013).

Graphology may be divided into graphical approach and segmentation approach. Based on the combination of handwriting and signature, authors predicted personality using graphical approach (Djamal, Darmawati, & Ramdlan, 2013a). They collected data from 25 writers and performed vertical, horizontal, and line segmentation for classification; five features of handwriting, page margin, spacing between words, spacing between lines, dominance of vertical zones, and baselines were considered along with nine features of signature. They applied greyscaling and thresholding. For simple structure patterns, they used a multi-structure algorithm, whereas, for complex patterns, they recognized the features using ANN with multi-layer perceptron (MLP); for handwriting features, only baseline was recognized using ANN here. Authors collectively received accuracy of 87–100% for a total of eight features using the multi-structure algorithm and 52–100% for a total of six features using ANN (Djamal et al., 2013a).

There have been various understandings of handwriting and associated psychology. Some authors claimed that the handwriting strokes reflect written traces of each individual's rhythm and style; it may be possible to interpret the writer's character traits, emotional disposition, and social style using the standards of graphology (Djamal, Ramdlan, & Saputra, 2013b). Handwriting analysis is a graphical analysis; it can be of the structure type of writing or of the symbol or letter. The authors integrated these two approaches by dividing classification into three stages: pre-processing stage, letter recognition stage, decision-making stage (Djamal et al., 2013b). The input was taken from the writer in all capital letters in an application form; the first area consisted of 32 boxes and the second area was expected to be filled in with the writer's signature. The features included 156 types of 26 capital English letters. They used 100 sets of data for the testing purpose. For converting the acquired data into vectors, greyscaling, thresholding, segmentation, and normalization were applied to the scanned images. From the first area of the application form, each of these handwritten letters was classified. Authors applied learning vector quantization (LVQ) and derived three dominant personality traits. Five features of the signature were identified using ANN whereas the other four features were identified using a multi-structure algorithm. They received an accuracy of 43% for LVQ. Signature recognition using ANN and multi-structure algorithm gave 56–78% and 87–100% accuracy, respectively (Djamal et al., 2013b).

Different techniques have been adopted by many researchers. Segmentation method using SVM was used to predict human personality from handwriting in Raut and Bobade (2014), Bobade and Khalsa (2015). They extracted various features such as pen pressure, baseline, size, spacing between letters and words, margin, speed of writing, slant of words and letters. However, the classification using linear and polynomial kernel functions with SVM provided prediction results with poor accuracy (Bobade & Khalsa, 2015; Raut & Bobade, 2014).

A study on how the human brain communicates through handwriting was conducted (Jabbar & Khiyal, 2015). Authors differentiated between good and bad writer characteristics based on five intelligence factors which were chosen appropriate words, common words, preposition analyzer, case-sensitive characters, and vowel analyzer. They proposed brain study analyzer using handwriting (BASH) where they classified using SVM with RBF kernel. They achieved accuracy of 98.1% and 98.4% for good and bad writers, respectively (Jabbar & Khiyal, 2015).

Using Minnesota Multiphasic Personality Inventory (MMPI) test (Dahlstrom & Welsh, 1960), authors proposed for personality trait identification (Fallah & Khotanlou, 2015). Authors pre-processed the scanned images of handwritten samples by reducing noise, contour smoothing and thinning. They binarized ruler and paragraph as well and segmented size of characters and words. They extracted text independent features like margin value, word expansion, character size, line space, word space, word tilt, line tilt, and horizontal to vertical ratio of characters; they also extracted a text-dependent feature, high-order local auto-correlation (HLAC) (Fallah & Khotanlou, 2015). To increase the space and resolution of different classes, generalized discriminate analysis (GDA) was carried out (Arica & Yarman-Vural, 2001). For the input images, corresponding output images were created using an MMPI personality test which were then provided to MLP neural network (NN). Here, the authors experimented their proposed system with 70 individuals; they belonged to different educations, ages, and genders. Authors achieved an efficiency of 76%.

For automated handwriting analysis, another approach adopted feature vector (FV) matrix and k-nearest neighbour (kNN) classifier (Joshi, Agarwal, Dhavale, Suryavanshi, & Kodolikar, 2015). Authors used polygonalization, thresholding, and template matching for extracting features such as baseline, letter slant, height of t-bar, and margin. The dataset was generated using 100 handwriting samples and the samples were examined by graphologists. They created FV matrix for a new sample of handwriting and classified its trait using kNN (Joshi et al., 2015). They suggested that such system would be able to assist an employer in deciding the suitability of a candidate for certain job.

Though an individual's nature varies somewhat from occasion to occasion, it is likely to maintain its core consistency. Authors proposed an approach to predict personality trait using mood invariant handwritings in Asra and Shubhangi (2015). They collected 500 samples from people belonging to different work environments; three paragraphs were given to write. To ensure the results to be time and mood invariant, they collected these samples on different days, at different points of time. Authors pre-processed the scanned images by cropping into single lines, de-noising, resizing, thresholding, and converting grey images to binary images; using bounding boxes they extracted features such as up-hill, down-hill, and constant lines. They used SVM and ANN on 200 samples and concluded that SVM outperformed ANN with 98% performance.

Study on determining personality traits based on MBTI was carried out where the author proposed three-level architecture: base, intermediary, and last levels (Gavrilescu, 2015). He determined handwriting features in the base level after applying normalization and character splitting. The intermediary level contained four NNs representing, E/I, S/N, T/F, and J/P according to four dichotomies of MBTI. Author extracted features such as baseline, writing pressure, word slant, connecting strokes, lower letter 't', and lower letter 'f'. The last level contained NN for training and testing purpose. 64 subjects were asked to take MBTI questionnaire repeatedly every two weeks for two months. From each participant, the author also collected handwritten samples written in Romanian language; samples contained three letters of 100 words each (Gavrilescu, 2015). While testing predefined handwritten sample texts, the achieved accuracy was of 86.7% whereas testing random handwritten texts from the same subjects provided an accuracy of 78.8%.

For handwriting analysis, an improved method used segmentation, baseline, and writing pressure detection (Bal & Saha, 2016). They binarized the scanned image using Otsu thresholding (Otsu, 1979) and the salt and pepper noise was removed using median filter technique (Premchaiswadi, Yimgnagm, & Premchaiswadi, 2010). Horizontal and vertical projection histogram techniques were used for line and word segmentation, respectively; skew normalization was performed as well. The writing pressure was measured with the standard deviation (Bal & Saha, 2016). As compared to other authors who had used in-house datasets, (Bal & Saha, 2016) used 500 handwritten text images containing 3800 words from the public IAM database (Zimmermann & Bunke, 2002) and achieved correct segmentation of 95.65% for lines and 92.56% for words using the proposed rule-based algorithm and correct normalization of 96% was achieved.

Enneagram is a psychological method that uses a series of questions to determine an individual's personality. Some of the researchers have considered it to be providing accuracy as high as 80–87% (Eric & Thomas, 2016; Riso & Hudson, 1996). Authors have proposed a system to assess personality using enneagram-graphology techniques (Pratiwi, Santoso, & Saputri, 2016). They converted the scanned image into greyscale colour and applied thresholding. They used Fuzzy C-means to form clusters of baseline, slant, breaks, and size features. The data were collected using 90 questions and an empty column to be filled with handwritten text. A total of 49 samples were examined using graphology and by an enneagram psychologist (Pratiwi et al., 2016). The match rate of 81.6% was found between both the examination techniques. Authors concluded that implementation of graphology is likely to be faster than applying enneagram as it does not require a series of questions and multiple psychological tests (Pratiwi et al., 2016).

For automatic analysis of handwritten documents, feature extraction is a crucial part. Authors have elaborated various features and techniques to extract them in Mukherjee and De (2016). The feature extraction may be performed globally, i.e., from the document page as a whole and locally, i.e., from the small units of writing. Authors have considered zone of writing, size, spacing in terms of words and letters, skew of writing, baseline, slant, pressure, margin, and signature features and have illustrated algorithms to extract them (Mukherjee & De, 2016).

For humans, neatness of handwriting is subjective. The visual aesthetic property of a handwritten document can be analyzed by a system. For this purpose, two levels are coarse level and fine level. Coarse level considers the overall layout, space usage between lines, words and margins whereas fine level includes aesthetic properties such as construction of each word, stroke smoothness, repeatability of similar strokes and other details such as consistency. Authors have analyzed the visual aesthetic of handwritten document images in Majumdar, Krishnan, and Jawahar (2016). They assessed fine-grained features like connected components, stroke, gradient, binary, and texture and coarse-grained features such as statistical and Fourier. The pre-processing step included binarization and masking using tight bounding boxes. They developed an in-house dataset including 1200 handwritten pages from 100 writers. They employed 18 individuals to annotate these documents manually using a 5-point Likert scale wherein neatness is one of the key features. They performed classification using linear SVM and regression using SVM with RBF kernel. The highest accuracy of 48.03% was achieved using statistical and Fourier features (Majumdar et al., 2016).

Another approach for automated handwriting analysis was carried out using six features including baseline, size, tittle over lower letter ‘i’, word spacing, margin, and slant (Sen & Shah, 2017). Authors collected samples on a white A5 sheet, written by subjects from an age group of 20–40 years. They applied image processing techniques; testing on 75 samples provided 95% accurate results.

Identification of human behaviour may be possible even with single feature extraction. Such an approach was developed where the cursive O was considered for behaviour analysis through handwriting (Asra & Shubhangi, 2017a). Authors divided the work into the training and testing phases. For the scanned input images, words containing ‘O’ and/or ‘o’ were taken into consideration. They pre-processed the image with colour conversion and resizing. The RoI was used for segmenting the middle loop of the letter using the drop fall algorithm (DFA) (Rui, Jie, Yunhua, & Yunyang, 2009). The segmented letter was passed through Freeman chain code (FCC) and zoning for feature extraction. They used SVM for training and testing; the dataset consisted of 500 samples of male and female adults within the age group of 18–77years. The accuracy of 86.66% was achieved. Their approach was developed for an isolated character ‘O’, however, they suggested that two or more letter words could be used for analysis (Asra & Shubhangi, 2017a).

Handwriting margin is considered to be revealing many aspects. Authors used 10 features of margin for identifying personality traits from the handwritten samples (Asra & Shubhangi, 2017b). They collected 500 samples from males and females within the age group of 18–75 years, regardless of their socio-economic status. They pre-processed the scanned images by thresholding using Otsu’s method (Otsu, 1979), converting into a binary image, and applying image dilation. They used SIFT feature (Sun, Zhao, Huang, Yan, & Dissanayake, 2014) and Zernike moment (Khotanzad & Hong, 1990) for feature extraction. The SVM classifier gave performance as high as 95% (Asra & Shubhangi, 2017b).

Using sub-features of margins, another group of authors analyzed personality using an Android-based mobile application (Wijaya, Tolle, & Utaminingrum, 2018). They pre-processed and segmented the handwriting image and extracted features for top, bottom, left, and right margins. They used 42 handwritten samples with SVM and achieved an average accuracy of 82.74%. They also compared their application outcomes with the observations given by experts.

Handwriting may be considered as a physical process which consists exhibiting yet silent gestures (Kacker & Maringanti, 2018). As a different approach than copying the predefined text, these authors collected 50 handwritten samples where the contents were written on the basis of the thought process of the writers. They applied thresholding, resizing and thinning algorithm on the scanned images and segmented them to extract features. Those features included margin, size, slant, degree of connection between the letters, spacing between lines, and ratio of the three vertical zones (Kacker & Maringanti, 2018). They mapped them to four MBTI dichotomies. They suggested that a detailed report could be generated by linking the results to an existing dataset.

The generalized flow for computerized graphology is summarized in Fig. 22 wherein the process begins with data collection which may be carried out on an online or offline basis. The publically available dataset such as IAM database (Zimmermann & Bunke, 2002) may be used or an in-house dataset may be created. An in-house dataset creation includes respondents who would write down a sample text on a paper and such samples in handwritten formats need to be scanned for preparing a database. Scanned samples then undergo pre-processing steps and necessary features are extracted from them. The features are then given to the respective personality prediction model; a model may be based on various approaches as shown in Fig. 22; the training and testing steps along with validation are chosen accordingly. The predicted personality trait is further given to measure performance accuracy and the personality prediction system can be utilized for graphology applications; an overview of the processing steps is graphically explained.

4.2. Datasets

Graphologists study a huge number of handwriting features and predict the writer’s personality based on it. On the other hand, computerized graphology requires learning through available data samples and extracting features for the writer’s personality prediction. Hence, valid handwriting datasets are desired.

Many researchers have worked with in-house datasets. The general steps may be derived as follows: choosing respondent group(s) which may include male-female ratio, age group, socio-economic status, profession; selection of template(s) to be written which may be given during the experiment or the respondents may be asked to write on their own, the language of writing is important too; specification of paper size such as A4 or A5, whether margins and lines are provided on it, pen type such as ink pen or ballpoint pen and colour of the ink; surface on which the text would be written on the given paper and the allowed duration for writing it; the day and time of this experiment as well as the number of times this procedure is repeated with the same respondents; the collected samples need to be scanned and digitally stored, hence, specifications of the scanner are important too. Large databases plan a significant role in handwriting-based systems. Developing a new database is generally time consuming and expensive. Also, such databases need to be validated for the performance measure. Hence, reusing the existing valid databases is preferable.

In Table 1, we have briefly summarized datasets generated and used in different computational graphology research work. Majority of the datasets are private and unpublished whereas IAM handwriting database (Zimmermann & Bunke, 2002) of English text has been kept public and freely available for research purposes. It is an offline database which contains images of cursively handwritten English text. It contains lines, words, and characters cropped from the sample data. Another available dataset is KHATT dataset (Mahmoud et al., 2014) of Arabic handwritten text. Such

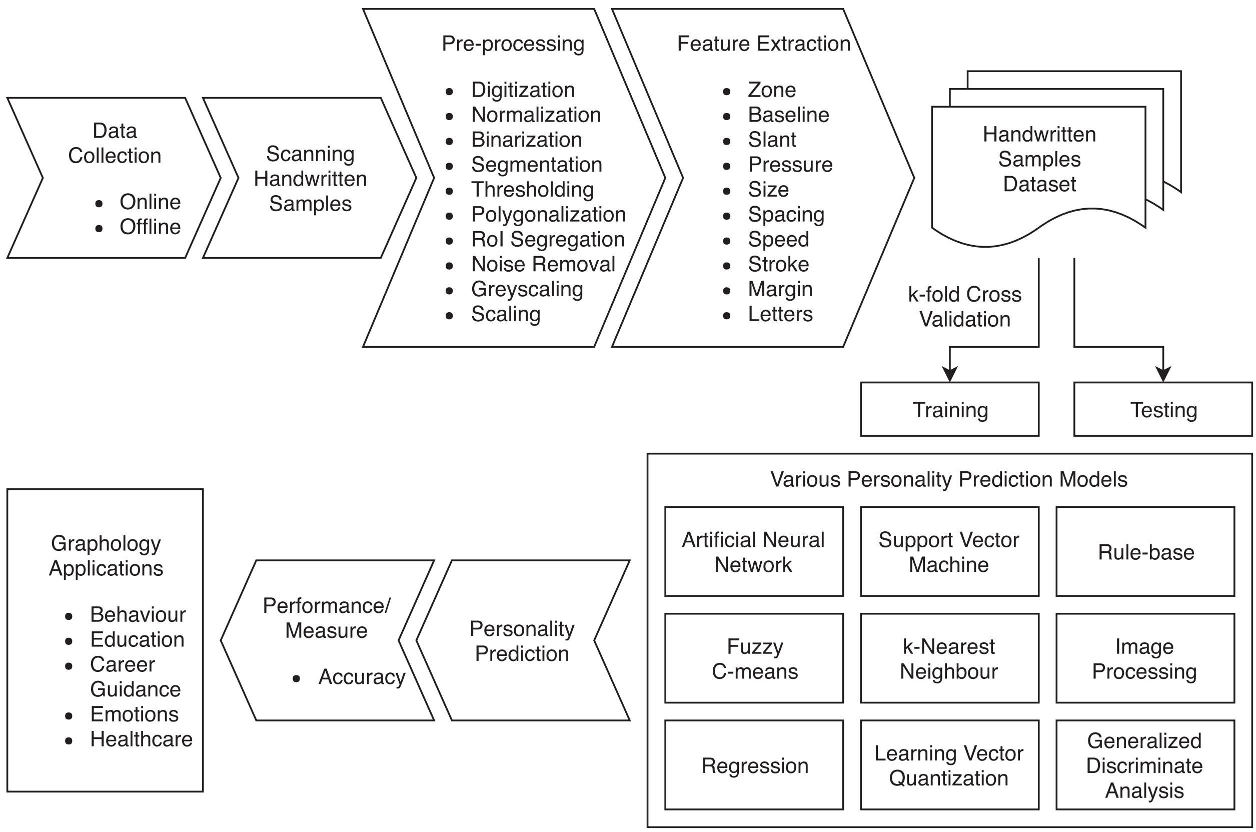

Fig. 22. Overview of handwriting-based personality prediction.

datasets are used for handwriting analysis and various applications. In Table 1, we have referred to these datasets of respective papers and discussed data collection methods, writing specifications, writer details, training and testing specifications and performance result.

5. Applications

Graphology has a vast range of applications. Handwriting is considered as a kind of behavioural biometrics (Xing & Qiao, 2016) which may be used for writer identification as well. Many researchers have worked with handwriting analysis and have studied how it can be useful in various domains such as employment profiling, healthcare to name a few. These applications may consider a set of handwriting features. In this section, we have briefly explained applications of graphology.

5.1. Education

Handwriting has been a crucial part of the education system. Analysis of handwritten text not only helps in behaviour prediction, but also helps identifying the development of children, their growth in school, and even detecting disorders in children. Tasks of drawing and/or writing by hands can also provide clinical profiling evaluations (Fairhurst et al., 2008). Evidence indicated that while not getting correct intervention, 10–30% of students suffer from hurdles in handwriting (Feder & Majnemer, 2007). A study was conducted among children to discover common and prevalent difficulties of handwriting (Sudirman, Tabatabaey-Mashadi, & Ariffin, 2011).

Handwriting is considered to be an activity which can highly improve young children's personality, basic coordination abilities and communication skills (Stefansson & Karlsdottir, 2003). An intelligent tutor was developed that helped to decide a suitable teaching strategy for a particular child by looking at his/her writing quality, personality, and emotional state (Albu, Hagiescu, Puica, & Vladutu, 2015). Using a tablet and a digital pen, the child's handwritten symbol and its two-dimensional space coordinates were acquired (Albu, Hagiescu, & Puica, 2014). This symbol was compared with the prototype symbol and evaluated based on the dynamic time warping (DTW) method (Kruskall, 1983). Also, the horizontal, vertical, angular and rotational distances were computed using corresponding integral projection vectors (Albu, Florea, Zamfir, & Drimbarean, 2008; Albu et al., 2014). The accumulated errors were calculated and compared to a threshold. A child's learning abilities and proficiency were measured. The authors also considered speech and emotion factor evaluation for predicting a child's personality trait (Albu et al., 2015).

Identification of personality, learning styles, and nature of students and teaching strategies of a teacher in Bali Kiddy School of Indonesia were conducted on the basis of graphology (Pithamahayoni, PUTRA, BUDASI, APPLIN et al., 2016). They experimented with 20 students of grade 5 and one teacher. Students were asked to write about their families; data collection through observation, MBTI questionnaire, and an interview was carried out. This approach identified 40% of the students to be sensitive and individual learners whereas 35% were found to be friendly and interactive. The remaining 25% of these students had perceiving natures; they had the tendency to look for new ideas and break the rules. The teachers may consider such factors so as to improvise their teaching strategies for a healthy development of the students. Such an approach may also be useful for the parents to support their children.

Table 1
Summary of datasets used for handwriting analysis.

Dataset Availability	Size of Dataset	Data Collection Method	Paper Reference	Training	Testing	Result
Private	Unspecified	Writing a few sentences on a plain white paper; scanning: 240 pixels per inch, 8 bits grey-scale resolution	(Sheikholeslami et al., 1995)	Unspecified	25 samples	Unspecified
Private	Unspecified	Unspecified	(Mogharreban et al., 2004)	Unspecified	Unspecified	Unspecified
Private	50 respondents	Filling questionnaire, writing a sentence; specification: black ink ball-pen; scanning: 600 dpi resolution; scaling: 800 × 100 pixel	(Mutalib et al., 2007)	80%	20%	Average accuracies: 90.27% (‘t’ recognition), 60% (ambition recognition)
Private	35 students	Unspecified	(Ahmed & Mathkour, 2008)	Unspecified	Unspecified	Unspecified
Private	Unspecified	Specification: same pen used by all writers; scanning handwritten samples	(Champa & AnandaKumar, 2009)	Unspecified	Unspecified	9 personality traits
Private	Unspecified	Scanning handwritten samples	(Champa & AnandaKumar, 2010a)	Unspecified	Unspecified	30 personality traits; performance: 0.099
Private	120 samples	Writing English paragraph; specification: same pen and paper; scanning: 1200 dpi resolution	(Champa & AnandaKumar, 2010b)	Unspecified	Unspecified	Consistent manual and computational predictions
Private	100 samples	Writing 70 – 80 words document; specification: plain paper without margins; scanning handwritten samples	(Prasad et al., 2010)	Test-1: 2/3rd data; Test-2: 99 samples	Test-1: 1/3rd data; Test-2: 1 sample	Accuracies: 90.3% (step-1), 93.86% (step-2)
Private	30 people	Writing 100 words sample English text; specification: same blue ballpoint pen, A4 size paper, image taken with Nikon coolpix S610 camera; writers: age (20 – 24 years), all right-handed	(Kamath et al., 2011)	Unspecified	Calibration (50%), experimental verification	80% consistent manual and computational predictions
Private	50 writers	Scanning handwritten samples	(Grewal & Prashar, 2012)	50 samples	Unknown sample	MSE reduced with an increased number of epochs
Private	Unspecified	Scanning handwritten samples	(Rahiman et al., 2013)	Unspecified	Unspecified	Higher accuracy when decisions were guided by human
Private	25 writers (training), 100 writers (testing)	Writing simple text, giving signature; specification: unruled A4 size paper	(Djamal et al., 2013a)	Unspecified	100 samples	Collective accuracies: 87 – 100% (multi-structure algorithm), 52 – 100% (ANN)
Private	Unspecified	Filling 32 boxes of an application form; specification: A4 size paper; scanning handwritten samples	(Djamal et al., 2013b)	1560 samples	100 samples	Accuracies: 43% (LVQ), 56 – 78% (ANN), 87 – 100% (multi-structure algorithm)
Private	100 writers	Writing 50 words document; specification: plain paper without margins, image taken with Nikon coolpix S610 camera	(Bobade & Khalsa, 2015; Raut & Bobade, 2014)	Unspecified	Unspecified	Poor accuracy
Private	Unspecified	Scanning handwritten samples	(Jabbar & Khiyal, 2015)	Unspecified	Unspecified	Accuracies: 98.1% (good writers), 98.4% (bad writers)

(*continued on next page*)

Table 1 (*continued*)

Dataset Availability	Size of Dataset	Data Collection Method	Paper Reference	Training	Testing	Result
Private	70 samples	Writing a constant text paragraph, taking MMPI personality test; specification: filling forms in a specific time duration, forms without lines; scanning: grey-scale, 300 dpi resolution	(Fallah & Khotanlou, 2015)	50 samples	20 samples	Efficiency: 76%
Private	100 samples	Writers: age (20 – 35 years); scanning handwritten samples	(Joshi et al., 2015)	Unspecified	Unspecified	Identified by graphologists
Private	500 samples	Writing three paragraphs; specification: A4 paper, black ballpoint pen, writing on a hard surface; scanning: laser jet HP scanner with 300 dpi, dimension 2528×3507 pixels	(Asra & Shubhangi, 2015)	70%	30%	SVM outperformed ANN with 98% performance
Private	64 subjects	Writing three letters of 100 words each (The London Letter (Morris & Morris, 2000)); MBTI questionnaire: repeating every 2 weeks for 2 months	(Gavrilescu, 2015)	Test-1: 50 samples; Test-2: 48 samples	Test-1: 50 samples; Test-2: 16 samples	Accuracies: 86.7% (predefined samples), 78.8% (random samples from same writers)
Public	550 text images	IAM database (Zimmermann & Bunke, 2002); specification: colour and grey handwritten text images	(Bal & Saha, 2016)	Unspecified	Unspecified	Segmentations: 95.65% (lines), 92.56% (words); normalization: 96%
Private	49 samples	Answering 90 questions, writing in an empty column	(Pratiwi et al., 2016)	Unspecified	49 samples	Match rate of enneagram and graphology methods: 81.6%
Private	Unspecified	Scanning handwritten samples	(Mukherjee & De, 2016)	Unspecified	Unspecified	Unspecified
Private	1200 samples	Writing on a set of topics	(Majumdar et al., 2016)	60%	40%	Highest accuracy with coarse level: 48.03%
Private	75 samples	Writing sample paragraph on white A5 paper; writer: age (20 – 40 years); scanning: 300 dpi resolution	(Sen & Shah, 2017)	30 samples	75 samples	Accuracy: 95%
Private	500 samples	Writer: age (18 – 77 years); scanning: 300 dpi resolution	(Asra & Shubhangi, 2017a)	Unspecified	Unspecified	Accuracy: 86.66%
Private	500 samples	Writing at different points of time in different days; specification: A4 paper, black ballpoint pen, writing on a hard surface; scanning: laser jet HP scanner with 300 dpi, dimension 2528×3507 pixels	(Asra & Shubhangi, 2017b)	Unspecified	Unspecified	Samples were classified from 1 to 6 based on margins
Private	42 people	Writing sample text; scanning handwritten samples	(Wijaya et al., 2018)	Unspecified	Unspecified	Average accuracy: 82.74%
Private	50 samples	Writing sample text; specification: A4 size plain white sheet, black ink; scanning handwritten samples	(Kacker & Maringanti, 2018)	Unspecified	Unspecified	Detailed report can be generated

5.2. Career

Selection of an appropriate career is an important task; its suitability can be associated with an individual's personality trait. Using handwriting-based personality identification and/or assessing personality through graphology tests is an individual's or a company's choice. Graphology is considered to have three main elements including research, interpretation of handwriting, and forensic comparison and identification of handwriting.

Authors have reviewed five computer-aided online handwriting analysis systems majorly for commercial purposes (Ow et al., 2005). Jerral Sapienza's Self-Analysis system asked questions about different aspects of the target handwriting and it generated a text-based report; this system is currently not taking any sample for assessment. Another system, named Andy Hunt's Graphonomizer, is currently active and generates a text-based as well as a graph-based report; it considers eight personality traits including independence, assertiveness, submissiveness, perfectionism, ambition, aggression, extraversion, and worldliness. The Handwriting University's Handwriting Wizard is also currently active where nine handwriting characteristics are considered: slant, size, stem of lower letter 'd' and 't', lower letter 'o', random strokes, humps of letter 'M' and 'N', height of t-bar, shape of lower loop or tail of letter 'y' and 'g', and margin and spacing; it generates a text-based report. Other two systems included Sheila Lowe's Handwriting Analyzer and Garth Michaels' Handwriting Analyst (Ow et al., 2005); they provided paid reports. Authors concluded that the overall procedure of graphology may not be replaced by the computerized system, however, collection of data, accessibility, retrieval, investigation and report generation may be carried out by a computer system for ease of further development (Ow et al., 2005).

Based on personality, job compatibility can be identified too. For evaluating an active personality and leadership characteristics of a writer, a model was developed by Coll et al. (2009). It was intended to serve employment profiling for a human resources (HR) managing company. Such companies aim to identify candidates with skills such as activeness, work motivation, leadership along with technical expertise. The proposed model considered 25 features such as slant, slope, line spacing, margin, script size; the pre-processed images were applied to NN. Authors collected 98 samples from people belonging to age between 12 and 85 years, irrespective of their gender or socio-economic status. The samples contained the text of around 90 words in the native languages including Catalan, Spanish, and English. They achieved 89% correct classification ratio (Coll et al., 2009). Such a model can be useful for HR professionals to improve selection filters during the recruitment process.

5.3. Emotions

There are various emotions that one encounters in his/her routine life. One of them is feeling anxious when a critical event occurs. Many studies have mentioned reading anxiety and its strong association with reading behaviour and levels of reading strategies (Babler, 1991; Oh, 1992). The emotional states have an impact on the handwriting styles. Personal characteristics such as emotional transitions, fears, honesty can also be extracted from one's handwritten text; one's mood and nature may also be inferred from the handwriting (Ugurlu, Kandemir, Carus, & Abay, 2016).

Authors considered the scenario of examination where the students generally experience anxieties (Ugurlu et al., 2016). They built a model to mark if the students were anxious or not. They divided the task into three parts: an ordinary day, a month prior to an exam, and the exam day. The handwriting features, line slant, character pixel height and width were considered. They experimented with 210 handwriting instances and constructed J48 decision tree. They correctly classified 66.66% instances (Ugurlu et al., 2016). They concluded that identification of a person's being under pressure during a critical event and estimation about his/her emotional states could be possible using the handwriting features.

Preventing suicide attempts have been one of the major public health concerns worldwide. An approach of identifying emotions that might symbolize suicidal behaviour was carried out where authors outlined 15 different emotions (Desmet & Hoste, 2013). The dataset contained suicide notes written by 1319 people in which (Pestian et al., 2012) found the most frequent labels to be instructions, hopelessness, love, information, and guilt; though instructions and information are not emotions technically, it was believed that in a suicide note, presence and distribution of such words might give hints for further examination and investigation (Shapero, 2011). For six most frequent emotions including thankfulness, guilt, love, information, hopelessness, and instructions, authors achieved F-scores above 40% whereas the overall classification performance scored up to 68.86% F-score (Desmet & Hoste, 2013).

Considering worry as one of the important parts in majorly everyone's life, authors evaluated left-handed and right-handed writers in terms of worry assessment (Mudaliar, Bhandari, & Dabholkar, 2017). They analyzed handwriting samples for pen pressure, size of words, slant of words, spacing between words, shape of letters, and page margins; for left-handed and right-handed writers, 50 samples each were used to determine personality traits and the range of worry. They identified that pen pressure, size of words, and the level of worry were not significantly different for both kinds of writers.

5.4. Healthcare

An individual's health may get reflected from various features such as eyesight, mental stability, physical strength. Handwriting is considered as the brain writing. Tiny neuromuscular movements occur unconsciously while writing. Hence, personality trait can be inferred based on the handwriting. Also, some of the body related facts can be identified using one's handwriting features.

The forensic science literature has described an abnormality in handwriting with manifestations due to the intoxication of alcohol. The handwriting of an alcoholic writer was found in the state of withdrawal; it is a state of tension which results in irregularity, ataxia, and tremor characteristics in the handwriting (Beck, 1985). Hence, an individual's characteristics and habits must be considered prior to predicting his/her personality based on graphology. This is because abnormal handwriting creates issues in evaluating authenticity. However, it can be used to judge the state of sobriety of the writer (Beck, 1985).

Depression is one of the leading causes of disability. Such a state may also get reflected in an individual's handwriting. The neuromuscular disorders rehabilitation can be diagnosed by measuring the movement smoothness of handwriting (Liu & Wang, 2013). Authors have presented an approach to measure movement smoothness. They found differences in seven metrics between the neuromuscular disorders and the normal people; these metrics can be used to evaluate recovery in the later phase of the patient (Liu & Wang, 2013).

5.4.1. Heart disease

Using handwriting analysis, heart disease can also be predicted (Kedar et al., 2016). Various methods like ECG training, blood sample analysis, chest X-Ray, etc. can be used to detect heart disease (Dangare & Apte, 2012). However, these approaches can be helpful only when physical symptoms are detected. A research study showed that handwriting can provide information about the individual's health. It has been observed that certain warnings can be obtained from one's handwriting during the pre-illness phase. Such warnings may be recorded even before the detection of actual symptoms of the disease can be found by any test (Kedar et al., 2016). Here, features such as right and left slants, total number of right and left slant lines, horizontal and vertical lines, total length of horizontal and vertical baselines, pen pressure and size were extracted from each zone of image segments for receiving fine details from the image (Gaurav & Ramesh, 2012). The extracted features were combined and classified using kNN algorithm. Authors predicted in one of these four classes: heart disease, low blood pressure, diabetes, and control group (Kedar et al., 2016). They achieved an overall accuracy of 75% with 40 training samples and 20 testing samples.

On the basis of handwriting, a three-layered architecture was introduced to determine blood pressure levels of individuals (Gavrilescu & Vizireanu, 2017). Authors used four handwriting features: baseline, lower letter 'f', connecting strokes, and pen pressure. They defined the associations of blood pressure levels and these handwriting features. They experimented with 18 subjects with age between 18 and 45 years. They tested with intra-subject and inter-subject and concluded with 84% and 78% accuracies, respectively (Gavrilescu & Vizireanu, 2017).

5.4.2. Parkinson'S disease (PD)

It has been found that some diseases can be traced from an individual's handwriting; PD is one of them. A frequent hallmark of PD is micrographia, which can be considered as the decreased letter size while writing. PD influences a part of the brain that controls the body movements, known as substantia nigra (Drotar et al., 2013). Early research was carried out on the slowness of movement in PD. They encountered that an individual movement or motor programme progressively degraded as the sequence of writing was continued; the time to initiation slowed down as well (Marsden, 1989).

Patients having this disease exhibit disruption even while performing the practised tasks such as handwriting (Broderick, Van Gemmert, Shill, & Stelmach, 2009; Costin & Geman, 2013; Drotár et al., 2013; Marsden, 1989) and speech (Mekyska et al., 2011; Tsanas, Little, McSharry, Spielman, & Ramig, 2012); they often have hesitations, pauses, and delays in the components of the sequences (Bidet-Ildei, Pollak, Kandel, Fraix, & Orliaguet, 2011). Authors acquired handwriting samples to classify the PD subjects; they built a predictive model for diagnosis of PD (Drotar et al., 2013). For this purpose, they experimented with handwriting samples collected from 37 patients suffering from PD and 38 control subjects. Each subject was asked to accomplish the template of eight handwriting tasks. These tasks included Archimedean spiral, repetitions of letters, words written in the native language of participants, and the task of longer sentence (Drotar et al., 2013). These samples were collected using digitizing tablet in the x–y plane and in the pressure axis. They used SVM with RBF kernel. The accuracy achieved in classifying PD patients using these kinematic handwriting features was 79.4%.

A new model was developed using in-air trajectories during handwriting for efficiently diagnose PD which achieved classification accuracy over 80% (Drotár et al., 2013). They suggested that the conjunction of conventional on-surface handwriting and in-air trajectories could be used to maintain quantitative records of the patients, which can then be used by the treating doctor for analyzing long-term changes.

Apart from handwriting tests, researchers have also worked with drawing tests for clinical evaluation of children diagnosed with learning disabilities such as Down Syndrome (DS) (Vimercati et al., 2015), dyslexia and/or dysgraphia (Galli et al., 2018). Spiral drawing is also considered as an important performance indicator to identify people with multiple sclerosis (MS) (Longstaff & Heath, 2006). These research papers acknowledge that not only graphology but also spirography can be taken as a healthcare measure. Spirography is a standard test to measure performance degradation and tremor severity (Bain & Findley, 1993) where the spiral drawn from the center with an increasingly larger radius is evaluated to rate tremor severity (Longstaff & Heath, 2006).

5.5. Deception and behaviour

There are emotional circumstances where one may feel differently. For example, one may feel great happiness on achieving some target or may get depressed on losing money; one may fear getting punished or one may get angry at others. Such emotions and moods are likely to occur in one's lifetime; how he/she would react to such situations may largely be dependent on his personality characteristics. Researchers have worked upon understanding if events such as lying, losing self-control, or carrying out a violent behaviour could be identified from one's handwriting.

There are many people who lie about many things such as claiming to have faced heavy traffic as the reason for coming late to the office. Though liars have command over the number of their stories up to an extent, the way they tell those stories may reveal their underlying state of mind (Freud, 1966). There are certain ways in which an individual's words can reveal if he/she were lying. For example, relatives converse of a lost person in the present tense, unless they knew the missing ones were never going to come back (Adams, 1996). A liar needs to frame a false story in a convincing manner such that even the incidents that did not occur or the attitudes that did not exist must appear sincere (Friedman & Tucker, 1990). Authors studied lying characteristics and developed multivariate linguistic profiles of deception to predict lies (Newman, Pennebaker, Berry, & Richards, 2003). They suggested that researchers should consider non-content words such as particles, functional words, to explore personality traits. They pointed out liars tending to use small and less complex stories while framing them; these false stories contained more negative characteristics (Newman et al., 2003).

On the other hand, for handwriting-based lie detection, Tang (2012) proposed to focus on how people write, instead of focusing on what they write. He examined a scenario whether the manager could detect honest people's lies in a handwritten message. It was mentioned that for an honest person to lie in the handwritten form, he/she was most likely to deviate from his/her normal behaviour because of the internal, personal, psychological, emotional, or external temptations (Ariely, 2008; Mazar, Amir, & Ariely, 2008). The author examined 24 cases that covered 11 languages in Tang (2012) and identified eight psychological principles that could help to point out emotional changes and/or lies.

It was recommended that experts must consider personality, levels of self-control, and inclusive degree of psychopathic disposition to explain the abnormal behaviour of an individual (DeLisi & Conis, 2008). A group of authors evaluated various technologies to determine if a person's behaviour towards violence could be predicted using the handwriting features (Fisher, Maredia, Nixon, Williams, & Leet, 2012). They tried to experiment with Lewinson–Zubin assessment scales (Olatunbosun, Dancygier, Diaz, Bryan, & Cha, 2009) which provided L–Z analysis of the scanned images which could help determine rational, social-emotional, and instinctual personality traits (Niels, Grootjen, & Vuurpijl, 2008). However, they could not automate it for identifying traits leading to violent behaviour. They mentioned that certain characteristics could be inferred to find violent behaviour; a computer-aided system might also require other details of the questioned person such as his/her

Table 2
Summary of behaviour-based handwriting analysis.

Paper Reference	Feature(s)	Pre-processing	Input	Analysis	Dataset	Data Specification	Result
(Sheikholeslami et al., 1995)	Margins, line spacing, line direction, slant, zone ratios	Digitization artifacts removal, thresholding, guideline removal	Document	Syntactic pattern recognition with 50 rules	25 handwriting samples	Unspecified	Consistent output with graphologists" interpretation
(Mogharreban et al., 2004)	Baseline, slant angle	Unspecified	Document	Crisp, fuzzy	Unspecified	Unspecified	Unspecified
(Mutalib et al., 2007)	Lower letter "t"	Digitization, normalization, scaling, noise removal, binarization, segmentation	Character (letter "t") segmentation	ANN	50 respondents	Questionnaire, writing one sentence	Average accuracies: 90.27% ('t" recognition), 60% (ambition recognition)
(Ahmed & Mathkour, 2008)	Slant, baseline, speed, size, continuity, form, arrangement, pressure	Unspecified	Document	Rule-base	35 students' handwriting samples	Unspecified	Unspecified
(Champa & AnandaKumar, 2009)	Baseline, pressure	Polygonalization, thresholding	Character segmentation	Rule-base	Unspecified	Unspecified	9 personality traits
(Champa & AnandaKumar, 2010a)	Baseline, pressure, height of t-bar	Polygonalization, thresholding, template matching	Character (letter 't') segmentation	ANN	Unspecified	Unspecified	30 personality traits; performance: 0.099
(Champa & AnandaKumar, 2010b)	Baseline, pressure, height of t-bar, lower loop of letter 'y', slant	Polygonalization, thresholding, template matching, GHT	Document, character (letters 't', 'y') segmentations	Rule-base	120 writers; 120 handwriting samples	Writing sample text	Consistent manual and computational predictions
(Prasad et al., 2010)	Size, letter slant, word slant, baseline, pressure, letter spacing, word spacing	Noise removal, orientation correction, smoothing, opening, segmentation, dimensionality reduction	Line, word, character segmentations	SVM with RBF kernel	100 writers' handwriting samples	Writing 70 – 80 words document	Accuracy: 93.86%
(Kamath et al., 2011)	Size, baseline, pressure, slant, breaks, word spacing, margins, speed	RGB thresholding, RoI segregation	Document, line, word, character (letters 'd', 'h', 'l', 't') segmentations	Manual analysis by handwriting analyst; inferences are made	30 writers; age: 20 – 24 years, all right-handed	Writing 100 words sample text using blue ballpoint pen	80% consistent manual and computational predictions
(Grewal & Prashar, 2012)	Baseline, slant, pressure, lower letter 'f', lower letter 'i'	Polygonalization, thresholding, template matching	Line, character (letters 'f', 'i') segmentations	ANN	50 writers	Unspecified	MSE reduced with an increased number of epochs
(Rahiman et al., 2013)	Pressure, slant, baseline, size, word spacing	RoI selection with human intervention, resizing, cropping	Line, word, character segmentations	Least square linear regression	Unspecified	Unspecified	Higher accuracy when decisions were guided by human
(Djamal et al., 2013a)	Margins, word spacing, line spacing, vertical zones, baseline; 9 features of signature	Greyscaling, thresholding	Line segmentation	Multi-structure algorithm, ANN	25 writers (training), 100 writers (testing)	Writing text document, signing on A4 size paper without lines	Collective accuracies: 87 – 100% (multi-structure algorithm), 52 – 100% (ANN)

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Table 2 (*continued*)

Paper Reference	Feature(s)	Pre-processing	Input	Analysis	Dataset	Data Specification	Result
(Djamal et al., 2013b)	156 types of 26 capital English letters	Greyscaling, thresholding, segmentation, normalization	Line (application form), block (signature) segmentations	LVQ, ANN, multi-structure algorithm	100 handwriting samples	Filling 32 boxes of application form in all capital letters, signing	Accuracies: 43% (LVQ), 56 – 78% (ANN), 87 – 100% (multi-structure algorithm)
(Bobade & Khalsa, 2015; Raut & Bobade, 2014)	Pressure, baseline, size, letter spacing, word spacing, margins, speed, letter slant, word slant	Thresholding, smoothing, segmentation	Document	SVM	100 writers	Writing sample text	Poor accuracy
(Jabbar & Khiyal, 2015)	Chosen appropriate words, common words, preposition analyzer, case-sensitive characters, vowel analyzer	Unspecified	Document	SVM with RBF kernel	Unspecified	Unspecified	Accuracies: 98.1% (good writers), 98.4% (bad writers)
(Fallah & Khotanlou, 2015)	Margins, word expansion, size, line spacing, word spacing, word tilt, line tilt, ratio horizontal to vertical; HLAC features	Noise reduction, contour smoothing, thinning	Document	MLP NN, GDA	70 writers; different educations, ages, genders	MMPI personality test, filling out form without lines	Efficiency: 76%
(Joshi et al., 2015)	Baseline, letter slant, height of t-bar, margins	Polygonalization, thresholding, template matching	Document; line, character (letter 't') segmentations	FV matrix, kNN	100 handwriting samples	Unspecified	Identified by graphologists
(Asra & Shubhangi, 2015)	Up-hill, down-hill, constant lines	Cropping, de-noising, resizing, thresholding, binarization; bounding boxes	Line segmentation	SVM, ANN	500 handwriting samples	Writing 3 sample paragraphs on different days, at different points of time; writing on A4 sized paper with black ballpoint pen	SVM outperformed ANN with 98% performance
(Gavrilescu, 2015)	Baseline, pressure, word slant, connecting strokes, lower letter 't', lower letter "f"	Normalization, character splitting	Character segmentation	NN	64 writers	MBTI questionnaire every two weeks for two months; 3 sample letters of 100 words each	Accuracies: 86.7% (predefined samples), 78.8% (random samples from same writers)
(Bal & Saha, 2016)	Segmentation, baseline, pressure	Binarization, thresholding, noise removal, segmentation, skew normalization	Line, word segmentations	Rule-base	IAM database (Zimmermann & Bunke, 2002)	500 handwriting sample; 3800 words	Segmentations: 95.65% (lines), 92.56% (words); normalization: 96%

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Table 2 (*continued*)

Paper Reference	Feature(s)	Pre-processing	Input	Analysis	Dataset	Data Specification	Result
(Pratiwi et al., 2016)	Baseline, slant, breaks, size	Greyscaling, thresholding	RoI	Fuzzy C-means	49 handwriting samples	Questionnaire, writing in empty column	Match rate of enneagram and graphology methods: 81.6%
(Mukherjee & De, 2016)	Zone, size, letter spacing, word spacing, skew, baseline, slant, pressure, margin; signature features	Unspecified	Line segmentation	Local, global	Unspecified	Unspecified	Unspecified
(Majumdar et al., 2016)	Statistical, Fourier (coarse level); connected components, stroke, gradient, binary, texture (fine level)	Binarization, masking using tight bounding boxes	Document, line, word segmentations	SVM with RBF kernel	100 writers; 1200 handwritten pages	5-point Likert scale annotation by 18 individuals; each document annotated by at least 3 different individuals	Highest accuracy with coarse level: 48.03%
(Sen & Shah, 2017)	Baseline, size, tittle over lower letter "i', word spacing, margin, slant	Binarization	Line segmentation	Image processing	Writers' age: 20 – 40 years; 75 handwriting samples (testing)	Wring sample text on white A5 sized sheet	Accuracy: 95%
(Asra & Shubhangi, 2017a)	Cursive "o"	Colour conversion, resizing, segmentation	Character segmentation	SVM	500 handwriting samples; writers' age: 18 – 77 years	Writing on white A4 sized paper at different points of time	Accuracy: 86.66%
(Asra & Shubhangi, 2017b)	Margin (10 features)	Thresholding, binarization, image dilation	Document	SVM	500 handwriting samples; writer's age: 18 – 75 years	Unspecified	Samples were classified from 1 to 6 based on margins
(Wijaya et al., 2018)	Margins	Greyscaling, thresholding	Document	SVM	42 handwritten samples	Writing on A4 sized paper	Average accuracy: 82.74%
(Kacker & Maringanti, 2018)	Margins, size, slant, degree of letter connection, line spacing, and zone ratios	Thresholding, resizing, thinning	Document; line, word segmentations	Image processing	50 handwritten samples	Writing based on thought process; no copying	Detailed report can be generated

background history, race, birthplace, genes, social status, religious beliefs for efficient predictions (Fisher et al., 2012).

6. Discussions

In the past many years, usage of graphology for human behaviour identification has significantly increased. Many research groups have conducted surveys on various aspects of graphology. In Kedar et al. (2015b), some of the most commonly used handwriting features are elaborated with writing samples and personality trait specifications. Authors have explained various techniques to extract these features and classify the trait.

A systematic review of automatic personality assessment was conducted (Kedar & Bormane, 2015). Authors briefly explained the literature till year 2015 and showed a comparison of four approaches in terms of the input dataset size and accuracy achieved. These approaches included automatic personality assessment (APA); they considered wearable devices, social media, non-verbal communication, mobiles, and handwriting analysis for the task. These authors, along with a group of researchers, conducted a review on automatic recognition of emotions (Kedar et al., 2015a). They considered various methods, namely audio, text, and facial expression-based emotion recognition. They also discussed the Blue Eyes technology (Mizna, Bachani, & Memon, 2013). They explained various features and methods to extract them; they also provided generalized block diagram for classifying the emotion recognition system. In the recent survey on handwriting and computerized graphology, authors pursued an extensive work, including a wide range of research papers (Garoot et al., 2017).

According to Popper (1959), pseudoscience contains unverifiable theories claiming scientific credentials (Bird, 2006). In other words, it is claimed to be having scientific statements, beliefs, or practices, however, the same is incompatible with the scientific methods (Cover & Curd, 1998). On the other hand, it was men-

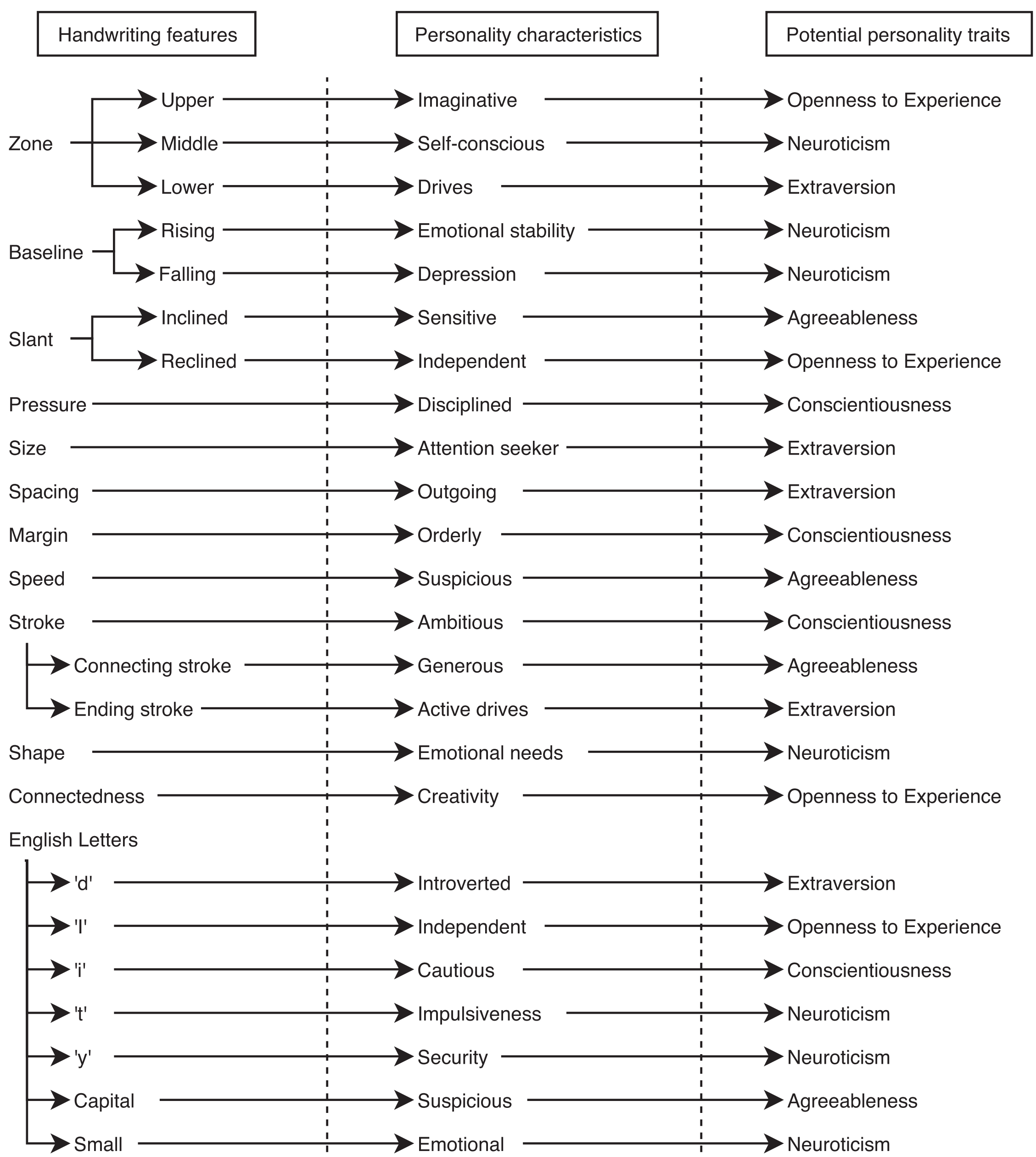

Fig. 23. Links between handwriting features, personality characteristics, and potential personality traits of FFM.

tioned in Pigliucci and Boudry (2013) that pseudoscience must involve some kind of emulation of science or some of its characteristics or appearance. Graphology, being considered as a pseudo-scientific study of handwriting (Kamath et al., 2011), needs to be validated as well. A major limitation of graphology is the lack of scientific validation for the correspondence between some handwriting features and respective personality traits. Mouly et al. (2007) conducted an empirical analysis to evaluate letters written by patients who attempted suicide. They identified the degree of accuracy between predictions provided by graphologists and internists who were not trained in graphology. They concluded that graphology can be taken as an additional discharge or decision-making tool in psychiatry or internal medicine (Mouly et al., 2007). An experiment was conducted to explore the key links between the underlying personality and its demonstrations in the handwriting among children (Gowda, Harish, Aslam, Padmanabiah, & Magaji, 2015). The researchers concluded that graphology may be an effective projective tool for an assessment of a wide range of traits Gowda et al. (2015). Also, a list of subjective validations is given in Ploog (2013), Brook and Chillis (2008). Though graphology may be debatable in some cases, these references may be enhanced further for respective applications.

In this section, we summarize our literature survey on behaviour-based graphology as shown in Table 2. We have included features, pre-processing steps, inputs, analysis techniques, datasets and their specifications. The results indicate accuracies, correlations, or consistencies for the specific research paper. We have linked the handwriting features with their respective personality characteristics. As shown in Fig. 23, we also provide how these characteristics may be linked with potential personality traits using FMM (Goldberg, 1990; 1993); the same may be linked to other models of personality trait measure. Such linked presentations can be useful in understanding the collective impact of these traits on an individual's personality.

7. Concluding remarks

The objective of this survey paper is to develop a clear understanding of the effect of handwriting on predicting personality traits. We have considered a majority of the handwriting features and respective personality characteristics as defined by the psychologists and/or graphologists. We conducted a survey on handwriting analysis and personality trait identification using handwriting features. For classifying personality trait, graphologists perform manual analysis, which consumes a significant amount of time and the accuracies are dependent on the knowledge and precision of the graphologists. Another limitation is that such analyses are prone to human errors. Hence, computerized graphology with minimum human intervention is required.

We have covered a wide range of research papers which include automated behaviour-based handwriting analysis where in general, the scanned handwriting samples have been pre-processed using techniques such as greyscaling, thresholding, conversion to binary images, noise removal, smoothing, thinning, and segmentation. These processes may differ depending upon the aim. Feature extraction is a major part where various techniques are applied to the pre-processed images. The research papers have covered graphological features such as slant, baseline, slope, margins, size of letters, pen pressure, line spacing, word spacing, and English letters such as lower letters 'f', 'i', 't', 'y' and their respective sub-features. It has been found that a large number of research works have been carried out on English as a language, however, some of the research papers include other languages such as Devanagari script, Arabic or Farsi languages.

There have been other motivations in terms of the development of computer-aided graphology. As handwriting is referred to as brain writing, some of the physical inferences can also be made by carefully examining handwritten samples. Applications such as personality-based career choice, HR recruitment, identification of early disorders in children's handwriting, detecting lies or violent behaviour through handwriting or identifying heart diseases or Parkinson's disease using the handwritten features may be targeted. In this survey, we have covered a list of applications that are associated with the handwriting features. Though graphology can help to identify the maturity of the writer, it cannot reveal his/her chronological age. Features such as slant, margin can help identify writer's inclination towards past or future, however, graphology can neither predict future nor explain the root-cause details for specific situation or action; graphology is not the process of forecasting. Also, writer's appearance such as eyes, hair or skin colour cannot be identified using his/her handwriting. This is why a graphologist needs to collect information about the writer apart from a handwritten text.

For estimating personality from the given handwritten sample, a majority of the research papers have only covered a few features from the set of available features. This has resulted in less specific categorization. Majority of the work has been carried out using non-public datasets wherein much of the work has compared automated results with the manual analysis. This leads to unavailability of the non-public datasets. Because the results of experimentation are highly affected by the dataset being used for the experimentation, availability of the datasets is desirable. It must be noted that the lack of scientific validation for the correspondence between some handwriting features and respective personality traits is the significant constraint of graphology. Hence, the existing approaches need to be improved in terms of feature extractions and having a clear mapping with the personality characteristics so as to develop more useful systems. Also, specific applications can be targeted in medical, forensics, education, and many other fields for providing better treatments; accuracy of the automated personality trait identification would be dependent on many such factors and such a system should be developed in association with the experienced psychologists and graphologists to reduce the error rates. On the other hand, it has been observed that a huge number of papers on computerized graphology have used an offline method to collect handwriting samples. Another way is to provide handwriting samples online where useful data such as pen grasping, starting and ending points, pen lifts, velocity, and other pen motion-related values may be captured. (Ancillao, Galli, Vimercati, & Albertini, 2013) developed such an approach based on optoelectronic which may be useful in clinical practices for evaluating motor and cognitive capabilities relying upon handwriting and drawing tests. We have observed that drawing test (Galli et al., 2018; Vimercati et al., 2015), spirography (Longstaff & Heath, 2006), and the Denver Development Screening Test (DDST) (Frankenburg & Dodds, 1967) are some of the clinically proven tests and may be utilized along with graphology for improved performance.

In future, researchers may consider a detailed study on graphology and relevant machine learning and deep learning approaches for building a reliable and robust computer-aided system.

CRediT author statement

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