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A framework for analyzing financial behavior using machine learning classification of personality through handwriting analysis

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ABSTRACT

Rigorous documentation and inspection methods are used by financial institutions to manage the risk due to information asymmetry and moral hazard. Nevertheless, the intent of the borrower of funds is not obvious. The unique nature of handwriting can to an extent be a reflection of intent.

Besides the financial services sector has a highly competitive market structure. Selling of financial products is a challenge; quickly understanding financial preferences through handwriting can be used to apply concentrated efforts on 'likely' customers. Handwriting analysis when facilitated through machine learning methods can have wider application to address the challenges of the financial sector.

The present study adopts an experimental approach to apply machine learning techniques to handwriting analysis. Identified handwriting correlates helped to map the individual into corresponding personality type. Risk preferences are mapped to the Big Five Personality Traits (Andreas Oehler, 2017). Thus the paper detailed the evaluation of handwriting features for one of the Big Five Personality Traits viz. Extraversion. The results yielded 7 such handwriting features which were evaluated with machine learning techniques on 112 samples collected through personally administered questionnaire. Extraversion is associated with perceived financial behavior as 'risk seeker'. We found that individuals who scored high on extraversion had no risk no reward philosophy, were likely to over spend and were inclined to invest in risky financial products like mutual funds.

1. Introduction

Handwriting of an individual is distinct and unique; even though the script may look similar but it is certainly not same as another individual's handwriting (Manimala S, 2016). Shrihari et al (2002) in their research on 1500 handwriting samples representative of U.S population established that every individual had unique micro features in their handwriting (Srihari S, 2002). The act of writing induces neural brain patterns leading to distinctive neural and muscular movement; these subconscious movements reflect in each individual's personality (Behnam Fallah, 2015). Researchers suggest that handwriting being a steady and personal medium of expression can provide clues to an individual's personality (Pedrabissi, 2009; Lazewnik, 1990; Warner Rebecca M, 1986). Handwriting can be said to be 'unique' and 'true' expression of personality and thus can be useful for counseling, forensic research, marketing, medicine, and personnel recruitment (Victor, 1952; Gardner, 1975; McNichol, 2007; SeemaKedar, 2015).

Each individual responds to a particular situation in a distinct manner. Successful predicting methods can help to understand how individuals behave in specific context or situation (Daniel J Ozer, 2006). Personality studies not only interest psychologists studying human behavior or relations (Hofstee W K, 2004), but are also useful to researchers working on decision making and policy formation.

Most financial theories have been based on the premise of rational decision making, with a focus on returns (Daiva Jurevičiene, 2013). However, around 1980s this rational approach started being questioned: it was found that basic economic postulates failed to adequately explain some of the inconsistencies in financial markets. This led several researchers from different disciplines to explore individual financial behavior for possible explanations of 'irrational' decision making.

The study of behavioral finance developed and encompassed both individual financial decisions and their impact on financial markets (McKenna, 2003; Borghans, 2008; Cliff Mayfield, 2008;

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Christelis, 2010; Thorsten Hens, 2010; Andrew Conlin, 2015). Several research studies have found that emotions can create distortions in cognitive attributes and financial behavior (Ising Alexander, 2007; Nila Firdausi Nuzula, 2019)

Such studies have attempted to understand investor behavior when rational models provide only partial explanation. Behavioral financial models developed to explain individual decisions have also been applied to analyze and explain unexplained or sudden variations in capital markets. Making investors aware of own personality traits, and how these traits guide financial behavior can lead to creation of wealth (Werner F.M. De Bondt, 1995; Runyanb, 2016; Greg Filbeck, 2017).

There is existing literature that links handwriting analysis (graphology) to personality traits (Branston, 1998; D. John Antony, 2008) and personality traits to financial behavior (Borghans, 2008; Brougham, 2011; David W. Johnstona, 2016). Larger number of these have dealt with the former relationship, i.e. association of handwriting features and personality traits (Hemlata, 2018; Lazewnik, 1990). There have also been few efforts to develop automated systems using machine learning to analyze and assess the personality of an individual using handwriting (Shitala Prasad, 2010; Behnam Fallah, 2015; Prachi Joshi, 2015).

The present paper aims to extract handwriting features from the handwritten text, and use these to predict the financial behavior of an individual. We use handwriting as an investigative tool, to measure the patterns of emotional reactions, conscious behavior and cognitive functioning as determined by the brain; all of which finds expression in handwriting. Applying exploratory research techniques, we attempt to analyze financial behavior through handwriting. We have collected data from over 200 participants, gathering handwriting specimens and their preferences to statements derived from the Big Five Personality Model (Robert R McCrae, 2008). Further, automated classification models for personality identification were explored through literature review and the possibility to validate these based on feature selection and machine learning techniques was tested. Application of machine learning techniques in this study is to add objectivity to the method, apart from the skill of the graphologist.

The study aims to establish that it is possible to predict financial behavior through analysis of personality traits and handwriting features. Once the method is fully developed the results can be useful in two ways: firstly, in the automation of the process by easy identification of handwriting traits of an individual without high human interaction, thereby reducing subjective biases reflected in other methods of personality evaluation. Secondly, it can be of use in tackling risks due to information asymmetry and moral hazard in financial markets, by providing an affordable method to assess credit risks by financial service providers.

The objectives of the paper are:

1. To identify suitable adjectives that qualify big five facets of personality in order to develop handwriting correlates.
2. To establish that handwriting features can be used to classify into the Big Five Personality Factors through literature review.
3. To develop a conceptual model for evaluating the use of handwriting analysis in studying financial behavior.
4. To explore the application of machine learning techniques to handwriting analysis and thereby relate handwriting features and financial behavior.

The paper is divided into four sections: the introduction is followed by the second section that deals with literature review to study the relationship between handwriting features and personality traits, followed by personality and financial behavior. The third section describes the research design and methodology of the study while the last section focuses on understanding how machine learning (ML) methods can be used to enhance the validity of the study. It also shows the results, discussions and conclusion of the exploratory study.

2. Background

2.1. Handwriting analysis & personality

The uniqueness of a person's handwriting is related to the particular personality; the individual habits can be reflected in his handwriting movements on paper, which can have significant deviation from copybook standards (Naftali, 1965). Abdul Rahiman et al. in their research paper "HABIT" argue that the micro-movements of the muscles due to brain neural patterns affect the personality depicted by individuals in daily activities like writing and drawing (Abdul Rahiman M, 2013). Researchers have correlated the personality traits of individuals to the features found in their handwriting. These features include baseline of writing, connecting strokes, letter slant, margin, pressure used while writing, size of letters, spacing between letters, words and sentences, speed of writing and upper and lower zones of letters (Victor, 1952; Gardner, 1975; McNichol, 2007; SeemaKedar, 2015). In handwriting analysis the handwriting strokes or features are identified and then assigned to the corresponding personality traits; using graphology, it is therefore possible to identify the personality of an individual and relate to financial activity or forensics (Hemlata, 2018)

An attempt at studying handwriting from the medical or neurophysiological point of view was made by the Hamburg psychiatrist Pophal (Pophal, 1949). On the basis of his work and that of other researchers like Muller, Enskat, Enke (Enke, 1938; Pophal, 1949; Naftali, 1965) it is possible to discern five elements which influence writing: inborn movement forms, acquired movement patterns, changing neuromuscular tension, mental image of the desired writing form and behavioral factors related to specific situation at time of writing the text. The inborn and acquired movement patterns show the innate traits of an individual, thereby enabling handwriting to be a good reflection of an individual's personality.

As listed above, the fifth element that influences handwriting is possible temporary physiological impairment of the central nervous system caused by any over-exertion, which may produce states of lower tolerance. This can be compared to the effects of great hurry; an urge to complete, which can make the writer impatient and careless in the execution of written forms. Anxiety poses as a special problem; it was shown by Pavlow (1926) and Sargant (1967) that there are two main responses to anxiety and breakdown under stress. One is the outward, direct and active form, causing excessive movements, while the other amounts to passivity, withdrawal and immobility. Consequently, in states of anxiety or great excitement, we may expect the handwriting forms to be either enlarged or the movements to be irregular, or forms that are reduced in size, shading, and firmness. Joy, on the other hand, usually makes the writing bigger and its flow smoother (Montello, 2018).

Reliability and validity of graphology and handwriting analysis have been studied (Blinkhorn, 1983) to identify personal attributes in personnel selection (Rafaeli Anat, 1983; Richard J Klimoski, 1983; Adrian Bangerter, 2009; Anderson Neil, 2010) and in predicting personality (Adrian Furnham, 1987; Pedrabissi Carla, 2009) stress (Giora Keinan, 1993), suicidal nature (Mouly S, 2007) and depression (Gaurav Harvir Singh, 2016; Marco Giannini, 2018). However, not many studies have been carried out for empirical validation of the findings.

Researchers have also experimented with handwriting analysis as a psychological assessment tool. Studies show a positive correlation between holistic graphological outcomes, clinical and personality assessment.[1] These suggest that graphology can be

[1] Based on Axis-I and Axis-II classification of Diagnostic and Statistical Manual of Mental Disorders-IV-TR, which includes psychological diagnostic categories and personality disorders respectively.

used for psychological assessment and diagnosis (Pierre E Cronje, 2013).

To build research background we have carefully studied several papers that have attempted empirical and experimental validation of the relationship between handwriting features and personality traits; Table 1 provides a summary of such studies, specifying their focus area and results. Most of the mentioned studies have worked with handwritten texts as sample. The exercise to develop the summary of literature helped - to identify existing gaps and develop a conceptual framework.

Based on studies conducted in the field of handwriting and psychology it therefore appears that a person's handwriting can act as a mirror of their behavior and personality patterns.

2.2. Personality & financial behavior

Individuals' financial decisions are not always easy to understand, but relating these to their personality can yield some acceptable conclusions (Andrew Conlin, 2015; Brougham, 2011; Cliff Mayfield, 2008). Studies have found that the psychological makeup of an individual comprises elements that motivate action or cause reaction; these can play a role in deciding if he is risk tolerant or risk averse (J Magendans, 2017). Tools for personality or psychological assessment like the Myers–Briggs Type Indicator or Keirsey's Instrument have been used to identify individual money management preferences based on responses to a standard set of statements (McKenna, 2003; Anthony Ma, 2017).

The relationship between big five personality traits model and financial decision making is well studied (David W. Johnstona, 2016; Robert G. Hammond, 2016; Pinjisakikool, 2017). The big five personality traits model was first developed by Lewis Goldberg in the 1960s as a theoretical psychology framework for analyzing personality. It was further validated by Robert McCrae and Paul Costa in 1987 (Grant Donnelly, 2012). This Five Factor Model (FFM) is widely used for personality research; herein researchers, have gathered the adjectives which can be utilized to represent individual personalities and classify into personality types.

The five factors model has been found to produce consistent results when applied in different research settings across cultures (Robert R McCrae, 2004). The theory specifies five factors that characterize individual personality types: Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness (Robert R McCrae, Empirical and theoretical status of the five-factor model of personality traits, 2008). Each factor is linked with behavioral patterns; for example, neurotic individuals may get easily irritated and be despondent, while extroverts are likely to be outgoing, friendly and talkative. Individuals with high score in 'conscientious' are more organized and self-disciplined, while those with high score on 'agreeableness' are modest, straightforward and compliant (Srivastava, 1999). The framework has also been applied to studies in behavioral economics and finance (Andrew Conlin, 2015; Julia Muller, 2017).

An individual's personality traits are defined by their behavioral and emotional responses to external stimuli. As the external environment and stimuli are diverse and ever changing, personality trait theory attempts to classify the recurring behavior and beliefs in contextually related circumstances (Andrew Conlin, 2015). As financial decisions tend to be repetitive they present distinct patterns for behavioral studies. The big five personality test is a frequently used classification to study personality and financial behavior (Julia Muller, 2017).

In financial decision making it is found that an individual scoring high on neuroticism or emotional instability is likely to have more debt (Nyhus, 2001) and will be prone to compulsive buying behavior (Hoch, 1991) while those having high scores on conscientiousness are more likely to participate in the stock market (Marco Bertoni, 2019). Other studies on the subject suggest that extraverted individuals often choose to take advice from a financial consultant, prefer to invest for short term gains (Cliff Mayfield, 2008) and boldly take exposure to stocks (Muhammad Zubair Tauni, 2017). On the other hand, researchers find that a nervous and insecure person tends to make risk free financial choices (Jonathan and Beauchamp, 2017).

A study based on data from Dutch households, found that the big five traits are associated to tolerance of risk. Extraversion and intelligence are positively correlated to financial risk tolerance; such individuals prefer to invest in risky financial instruments like mutual fund and stocks. Emotional maturity and agreeableness in individuals reduces financial risk tolerance; such persons are safe investors and prefer fixed income products over others (Pinjisakikool, 2017).

While taking important financial decisions, an individual's behavior and psychological makeup plays an important role. A study conducted by Yilan Xu et al (2015) concluded that "conscientiousness will be negatively and neuroticism positively associated with measures of financial distress, while higher levels of agreeableness would be associated with higher debt and lower earnings". (Yilan Xu, 2015). Several other studies that related specific personality traits to differences in financial decisions taken by individuals, also help to classify financial behavior into risk seeking and risk averse tendencies. A brief summary table of literature indicating association of personality traits and financial behavior is given Table 2:

Gokhan Ozer (2019) also have established that the personality traits of conscientiousness, agreeableness and openness to experience are directly related to financial behavior.

3. Proposed methodology: An exploratory experiment

3.1. Research purpose

It has been noted that "exploratory research is the initial research, which forms the basis of more conclusive research. It can even help in determining the research design, sampling methodology and data collection method" (Singh, 2007). Exploratory research "tends to tackle new problems on which little or no previous research has been done" (Brown, 2006). Our research is inductive in nature, wherein data is used to derive the working hypothesis that handwriting can be used to predict financial behavior. There are some studies that show the relationship between personality traits and financial behavior, but human intelligence can manipulate and create a barrier to gathering genuine responses. An individual may overstate or understate their response to conform to socially acceptable answers. It is to counter such conscious or even sub-conscious falsifying of personality traits and preferences that the development of specific set of handwriting characters to assess financial behavior of an individual becomes useful (Zhi Chen, 2017).

3.2. Experimental procedures

Data collection methods based on questionnaires and interviews are commonly used for studying financial behavior. Initial studies based on big five model have correlated personality traits and financial behavior using 240 item NEO Personality Inventory questionnaire (Robert R McCrae, 2008) while later questionnaires are based on 60 items i.e. the NEO Five Factor Inventory (Robert R McCrae, 2004). Although questionnaire is a popular survey tool it suffers from an inherent limitation; the participant may not want to reveal their true opinion, especially when they think that the response will not be of any benefit to them or when they

Table 1
Evolution of literature in handwriting analysis and personality studies.

Paper reference	Theoretical foundation(s)	Focus	Sample size	Results
Linton et al. (1962) (Harriet B Linton, 1962)	Handwriting analysis, Application of Tilting-room-tilting-chair (TRTC)[a] test to measure effect of external factors on behavior.	To investigate about the psychological correlates of secondary beginning strokes in handwriting.	53	The study predicted that those using beginning strokes in letters like n,m,and y were more likely to be lacking intellectual ability, would find it difficult to deal with different, unknown tasks and would be more anxious and impulsive.
Galbraith et al. (1964) (Dorothy Galbraith, 1964)	Handwriting analysis, Tests for personality traits	To investigate the stroke and patterns that are indicative of personality traits such as attention to detail, domineering, persistence, self-consciousness and stubbornness	100	The study counted the number of strokes and found that reliability was highest for the trait of domineering (.87) and lowest for stubbornness (.61)
Lemke et al. (1971) (Elmer A Lemke, 1971)	Handwriting analysis, Psychological measurement tests	To investigate the correlation between handwriting and personality of individual	103	Handwriting analysis was supplemented with psychological measurement tests e.g. Cattell's Sixteen Personality Factor, Edwards Personal Preference Schedule, etc., to conclude that handwriting features reflect personality.
Williams et al. (1977) (Michael Williams, 1977)	Handwriting analysis, Tests for personality traits	To investigate the relationship between handwriting features and Eysenck's Extraversion–Introversion and Kagan's Impulsivity–Reflectivity personality dimensions.	46	Few measures of rightward slant are related to the personality trait of extraversion while impulsive individuals tend to write quicker.
Klimoski et al. (1983) (Richard J Klimoski, 1983)	Handwriting analysis	To investigate the issues related to reliability and validity of different uses of handwriting analysis.	NA[b]	Based on earlier experiments and research concluded that handwriting remains relatively stable over a period of time and can be used as a reliable method of analysis. As inferences by different graphologists looking at the same handwriting were consistent, it was concluded that graphology can provide valid and useful insights into personality.
Warner et al. (1986) (Warner Rebecca M, 1986)	Handwriting analysis	Study of facial appearance, speech style and handwriting on personality.	NA	The study corroborated the earlier conclusions of differences about personality obtained from facial appearance, handwriting, and speech
Peeples et al. (1993) (E Edward Peeples, 1993)	Handwriting analysis, Tests for personality traits	To determine the feasibility of using handwriting to predict normal personality traits.	244	The study concluded that 13 personality traits out of 22 possible traits are predicted by 2 or more of the 15 handwriting characters.
Tett et al. (1997) (Robert P Tett, 1997)	Handwriting analysis, Tests for personality traits	To assess the effectiveness of graphoanlaysis in personality classification.	49	The study did not show encouraging results as only 6 of 119 predicted relations between personality and handwriting were positively correlated. Thus, further research on the subject was required.
Lowis et al. (2001) (Michael J Lowis, 2001)	Handwriting analysis, Personality traits	To identify handwriting feature that would indicate personality traits related to higher academic performance of a student.	100	The study identified that individuals with consistent right or left slant letters were significantly linked with high grade points, while letters that were upright or had wavering slants was not.

[a]The Tilting Chair Test is a perception test used to determine field-dependence or field-independence, a concept of cognition where individuals reference their own internal informational sources, or make reference to external informational sources when making decisions.
[b]NA-Not Available- Study based on literature review.

fear being penalized for their opinion (Zhi Chen, 2017). Studies based on analysis of handwriting to understand respondents' financial behavior can improve the authenticity of responses, as handwriting features cannot be easily camouflaged.

3.2.1. *Relationship between the research variables*

Fig. 1 represents the conceptual model relating to Handwriting, Personality and Financial Behavior. Existing literature finds that personality traits of an individual are likely to govern their financial decisions. However, as handwriting is a reflection of personality, the present study postulates that handwriting features can be used to study financial behavior.

3.2.2. *Research tools: Questionnaire designed to include specimens of handwritten text*

Our research tool is designed to have the advantage of cross checking the 'truthfulness' of response through handwritten text boxes. While the questionnaire was developed in the usual manner, it is the written text that not only enabled us to find handwriting features but also, evaluate the quality of responses (in terms of truthfulness) to some extent.

The questionnaire included questions to gather respondents' socio-economic characteristics, personality traits and financial behavior. Financial behavior was measured from statements like: I believe in no risk no reward philosophy, I buy things which I cannot afford, because I feel at some point it will all be fine, I

Table 2
Association of personality traits and financial behavior.

Big five personality trait	Paper reference	Analysis	Results
Extraversion	Oehler et al. (2017) (Andreas Oehler, 2017)	Regression methods	Individuals who are more extraverted tend to purchase riskier financial assets at higher prices.
	Sarah Brown et al. (2014) (Sarah Brown, 2014)	Probit regression	There is a positive correlation between the personality trait of extraversion and unsecured debt; e.g. extravert individual has a higher probability to own a credit card.
	Tauni et al. (2017) (Muhammad Zubair Tauni, 2017)	Probit regression	Individuals with high extraversion, conscientiousness and agreeableness score have higher frequency of financial information acquisition and thus, higher frequency of trading.
Neuroticism	Tauni et al. (2016) (Muhammad Zubair Tauni, 2016)	Confirmatory factor analysis (CFA), Structural equation modeling (SEM)	Individuals with neuroticism and openness personality traits look to advice in making investment decisions.
	Brougham et al. (2011) and (Ruby R Brougham, 2011)	ANOVA	Neuroticism is a trait related to compulsive buying.
	Xu Y et al. (2017) (Yilan Xu, 2017)	Regression methods	Personality trait of neuroticism is associated with financial distress.
	Sarah Brown et al. (2014) (Sarah Brown, 2014)	Probit regression	Neurotic individuals have a tendency to choose simple debt products like overdrafts.
Agreeableness	Nga et al. (2013) (Joyce and Nga, 2013)	Factor analysis	Agreeable investors have strong preference for socially responsible investing.
	Nyhus et al. (2001) (Ellen and Nyhus, 2001)	Factor analysis	Agreeable individuals tend to save less.
	Alessandro Bucciol et al. (2017) (Alessandro Bucciol, 2017)	Probit regression	Agreeableness is negatively correlated with financial risk taking.
Openness (open to experience)	Bortoli et al. (2019) (De Bortoli D, 2019)	Logistic regression	High score in openness are associated with greater likelihood of taking risk.
	S. C. Parker (2009) (Parker, 2009)	Literature review	Openness to experience is associated with entrepreneurship and such individuals can be described as risk tolerant.
	Mayfield (2008) (Cliff Mayfield, 2008)	Structural equation modeling (SEM)	Individuals who are open to experience are inclined to engage in long-term investing
Conscientious	Donnelly et al. (2012) (Grant Donnelly, 2012)	Hierarchical regression	Conscientious individuals manage money in a better manner.
	Sarah Brown et al. (2014) (Sarah Brown, 2014)	Probit regression	Highly conscientious individual may not want to buy or own a credit card.
	Richard L et al. (2007) (Richard L, 2007)	Literature review - Neuroscience	High scores on conscientiousness may lead up to better chances of success in stock trading.

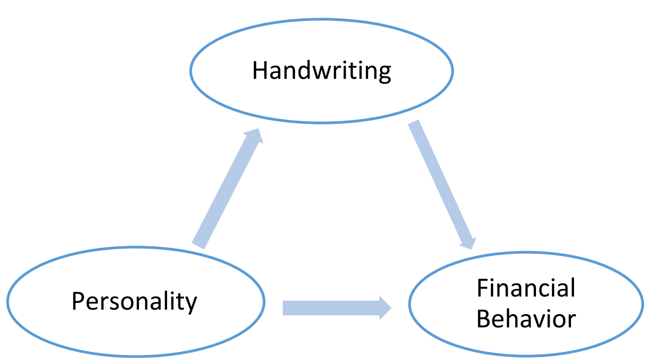

Fig. 1. Relationship between research variables.

often take loans to finance my spending, I often invest in stocks and mutual funds, etc. These statements were adapted from the work of du Plessis, Graham Alexander Du Plessis (2015) and Camilla Stromback (2017). Responses were coded on a five-point Likert scale as 1 for strongly disagree and 5 for strongly agree.

The five moderating variables considered in the study are the unique personality traits of agreeableness, extraversion, conscientiousness, neuroticism and openness adopted from the Big Five Personality Framework. In this study, we have utilized the Big Five Personality framework[2] (Robert R McCrae, 1992) to measure the personality dimensions of individual financial behavior. This framework is widely accepted in applied research on the subject (Barrick and Mount, 1991).

To ensure the robustness of data, respondents have been selected so as to meet requirements in terms of age, education, income, and financial literacy. The questionnaire has been designed to include sixty statements such that twelve statements are assigned to identify each of the big five traits (De Bortoli D, 2019). Along with these, there were three open ended questions and a predetermined text to collect an adequate sample of handwriting. The handwriting sample collected (predetermined text and random text) is as unique as a fingerprint and can be obtained easily. An individual's pattern of writing is reasonably consistent over a period of time even if there may be events that have an effect on the individual's lifestyle. Handwriting therefore exhibits potential as a fair assessment tool for different persons. It

[2] Big Five Personality Framework is explained in detail in next section on Identification of handwriting features.

cannot be claimed as an unfailing tool, but it is an appropriate and practical tool for the psychologist in understanding the human psyche (Mahesh Ramanina Gowda, 2015).

Handwriting features are quantitative measurements which can be used to infer significant description of the writing style. These measurements can be found from a lengthy handwritten text or from a small paragraph, word, or even a single character (Sargur N. Srihari, 2002).

It is common to analyze using existing essay or passages that have many of the common letter associations found in various English words including the use of capital letters of the alphabet, common punctuation, and the numbers "1" through "9" (Handwriting standards and disguise, 2019). In our research we have used "The London Letter"[3] originally designed by Osborn in 1929 (Ron Morris, 2000; Levinson, 2001; Heidi H Harralson, 2017) as a predetermined text, that can be copied by the individual participating in the study. Using a predetermined text can help ease the participant into a normal state of mind, while giving their handwriting sample. It can also be combined with freely chosen written expression (Mihai Gavrilescu, 2018).

3.2.3. Use of big five personality trait model

Many investigations in the past have converged on the basic structure of personality in the form of the Big Five Personality Framework (Goldberg, 1990), also known as the Five-Factor model (FFM) (Digman, 1990). It concludes that the five traits of neuroticism, extraversion, openness, agreeableness and conscientiousness captures the important domains of human personality (Widiger, 2015). These five domains have been identified in several empirical studies (Robert R McCrae, 2008) and have been shown to interpret patterns of behavior, such as well-being and mental health, job performance and marital relations (Ozer DJ, 2006). The Big Five Personality Framework has been used for a range of applications, including clinical assessments of personality disorders (Widiger Thomas A, 2013).

A study conducted by Deborah A. Cobb-Clark (2011) in Australia found that personality is stable over a four-year period. She applied the model to a sample of persons in the 20–55 year age group. Average personality changes were found to be small and did not vary noticeably across age groups. Thus, personality can be concluded as a stable input into many economic decisions (Deborah A. Cobb-Clark, 2011). As discussed in the earlier in the section, there are studies that find the big five model to be better than other psychometric tools like MBTI[4] (Fabio Celli, 2018) and increasingly larger number of studies use the robust five factor analysis. Thus, big five personality trait model can be suitable to use to study the linkage between personality and financial behavior.

3.2.4. Sample size

One of the studies conducted by Lavanya et al. using 50 handwriting samples, each of left and right handers of college students, concluded that the worrying pattern of left hand writers and right hand writers are different (Huwida E Said, 2000; Lavanya Mudaliar, 2017). In another research study GRAPHJ – a forensics tool for handwriting analysis was tested on handwritten samples, written by 10 individuals in cursive writing with similar ink and paper. Each subject was asked to write the same long paragraph of text that was said to them. The text had all letters of the Italian script, as well as sentences with varying length and complexity (L. Guarnera, 2017). Literature review as per Table 1 suggests that very large samples are not usually used for studies on handwriting analysis. Our study is based on a sample size of 200, based on convenience sampling technique.

3.2.5. Data collection

An introduction about the research purpose and sensitization about the importance of honest answers to the study was carried out by us before administering the questionnaire in respondents' workplace setup. Small talk before distributing the questionnaire also helps in removing any mood fluctuations that may reflect excessively in handwriting. Participants were allowed to choose the writing tool e.g. ball point, fountain pen or pencil of any color. The handwriting sample texts were processed for feature extraction as detailed subsequently in Section 4. The responses to personality statements and statements reflecting financial behavior were used to classify the corresponding samples into the personality types based on the big five personality model.

3.3. Identification of handwriting features

Existing literature shows that the big five model is widely used to understand financial behavior and thus, we have chosen that as our base model (Grant Donnelly, 2012; Muhammad Zubair Tauni, 2017). The big five personality traits have 6 corresponding facets and in the Big five taxonomy, these facets have defining adjectives. These adjectives form our basis to identify the handwriting correlates (Srivastava, 1999).

We have selected the big five personality factor of Extraversion to develop the details of corresponding handwriting correlates and handwriting traits. As given in Fig. 2, Extraversion has related facets as warmth, gregariousness, assertiveness, activity, excitement seeking and positive emotions and the correlated trait adjectives are outgoing, sociable, forceful, energetic, adventurous, and enthusiastic respectively (Robert R McCrae, 1992; Srivastava, 1999; Gerrit Mueller, 2006). Based on the correlated trait adjectives the appropriate handwriting correlates have been identified by us. Some of the trait words do not directly map with handwriting, a synonym is used in such cases. For example for the facet of gregariousness, the corresponding adjective is sociable. This is not directly mapped to handwriting characteristics; we therefore, use friendly for gregariousness which is identified with handwriting characteristics like broad loop 'e', rounded or large full lower loop 'y' or 'g'. By identifying handwriting correlates and related traits for all the big five factors, we thus, derived the conceptual model given as Fig. 2 Big Five Factor- Personality Facet- Handwriting correlate - Handwriting Features (BF-PF-HC-HF)

Based on this model developed by us, we can identify if an individual tends towards extraversion, when their handwriting depicts the traits such as ascending baselines (Ploog, 2013), connectedness (D. John Antony, 2008; Seifer, 2014; Gardner, 1997), fast writing (Gardner, 1997), high flying 'i' dot (Gardner, 1997), large letter size between 4 mm to 5 mm (Seifer, 2014), long crossing of bar in 't' (Gardner, 1975), right ward trend or right slant (Ploog, 2013), small word spacing (D. John Antony, 2008) and wide spaced letters (Klein, 2010).

4. Proposed data analysis

4.1. Handwriting trait selection and classification

The Big Five Factor- Personality Facet- Handwriting correlate - Handwriting features (BF-PF-HC-HF) model (Fig. 2) has also, enabled us to identify the financial behavior corresponding to each handwriting trait. For example an individual whose handwriting is having ascending baselines, heavy pressure, rightward

3 A standard request exemplar used by graphologists in handwriting analysis because the text is designed in such manner as to provide relevant information on all the handwriting features required for analysis.

4 The Myers–Briggs Type Indicator (MBTI) is an introspective self-report questionnaire that helps individuals to identify own learning and working styles.

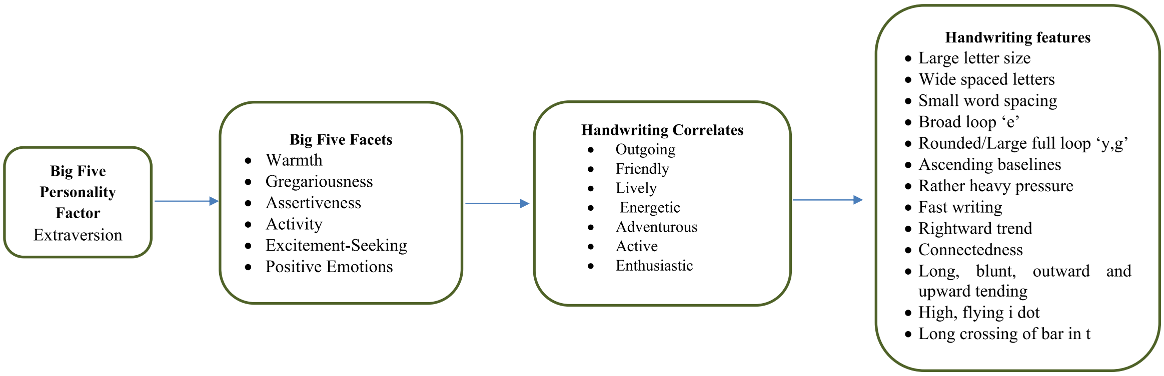

Fig. 2. Extraversion Big Five Factor- Personality Facet- Handwriting correlate - Handwriting features.

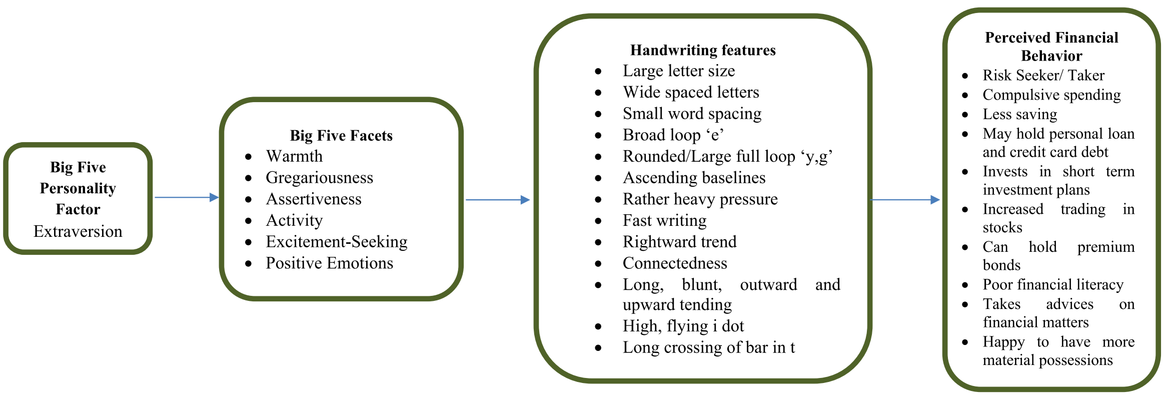

Fig. 3. Extraversion — perceived financial behavior based on handwriting features.

trend, wide spaced letters can display a financial behavior of compulsive spending (MFHA Guidelines, 2018) and create debts (Grant Donnelly, 2012; Nyhus, 2001).

Fig. 3 shows perceived financial behavior of an individual who has high scores in extraversion. The handwriting of such a person will generally have larger letter size, smaller word spacing, heavy pressure, rightward trend and so on, as depicted by the corresponding handwriting features. In similar manner, the handwriting features for each of the five personality types are selected and classified to map with their financial preference.

The model was further used to develop statements to assess personality traits for cross verification of the handwriting features. The questionnaire consisted of both action oriented and emotion based statements, developed on a 5 point Likert scale for personality trait assessment.

Initially the study analyzed handwriting features on 5 point scale to capture the nuances of handwriting features. However, large number of handwriting features did not match with the personality trait according to sequential numbering; it was thus decided to forego the 5 point scale in classification of handwriting feature and to adopt a binary scale, where 0 (zero) is used to denote deviation from the particular trait and 1 (one) to denote closeness to the specific handwriting trait. For example, if the handwriting has wide spaced letters it would suggest an outgoing personality (extraversion); hence, closed spaced letters are denoted by scale point 0 and wide spaced letters are denoted by scale point 1. Use of binary scale also, facilitates the application of Machine Learning (ML) techniques to Handwriting Analysis (Adeline Granet, 2018).

4.2. Computerized handwriting analysis

Early use of computer-aided graphology (CAG) was presented by G Sheikholeslami in the 5th international workshop on 'Frontiers in Handwriting Recognition at Essex, England in 1996. Using twenty five handwritten samples handwriting features were analyzed and mapped with interpretations using syntactic pattern recognition. Personality descriptions of the writers were given as output which was found to be consistent with graphologists' interpretation (G Sheikholeslami, 1996). Subsequently many researchers have applied computer science applications like image processing, support vector machines (SVM) and artificial neural networks (ANN) to introduce objectivity in handwriting analysis as a technique to analyze personality and behavior. Use of automation and computerization in handwriting analysis has evolved to an extent that several readymade software packages have been developed for the purpose. By combining the use of such software along with machine learning methods several applications of handwriting analysis have been developed. These methods have been used in forensic, psychological assessment and personnel selection etc. In a recent study Gavrilescu tested the individual's handwriting on a non-invasive, neural network based system and the accuracy of the results was found to be 84% (Mihai Gavrilescu, 2018).

We present in Table 3 the review of software to support the application of machine learning techniques to handwriting analysis (see Fig. 4).

The handwriting analysis softwares described in Table 3 can be used for handwriting feature extraction and identification, but their capacity is limited to handling around two dozen handwriting features, whereas there actually exist hundreds of handwriting features. Thus, it is more effective to adopt a hybrid approach, wherein handwriting features corresponding to each personality

Table 3
Details of existing software packages for handwriting analysis.

Software	Description
MovAlyzeR	MovAlyzeR (Neuroscript, LLC, http://www.neuroscriptsoftware.com/, Tempe, AZ) can record handwriting movements using a digitizing tablet connected to a computer. The software has research applications in kinesiology, psychology, education, geriatrics, neurology, psychiatry, occupational therapy and forensic document examination (Hans-Leo Teulings, 1997; Michael P Caligiuri, 2015).
CEDAR-FOX	It can be used for writer verification and identification, signature verification and identification, document property extraction and document sub-image retrieval from handwritten samples (Sargur N Srihari, 2018).
Masquerade	Masquerade is a software that helps to automatically measure the slant, size, pressure, zone and related features from the handwriting sample. Its use reduces the time required for accurate identification of handwriting features; helping the graphologist in producing reports in lesser time (Luca Guarnera, 2018).

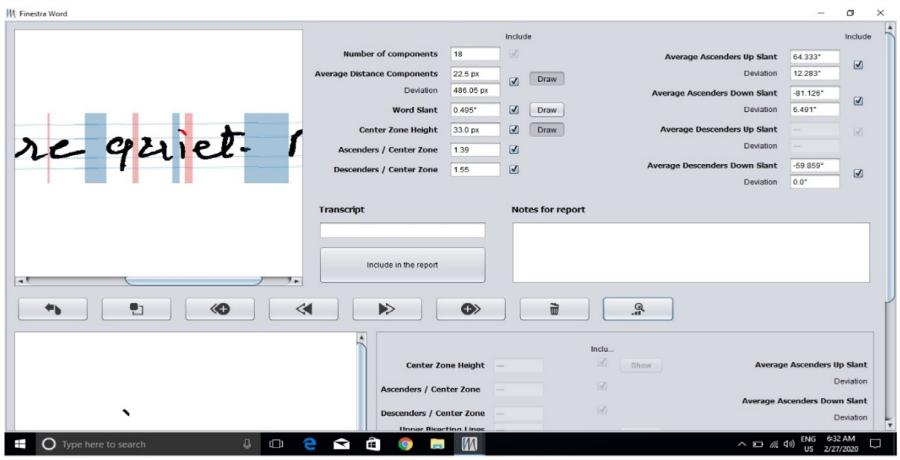

Fig. 4. Screenshot of word segmentation using masquerade handwriting analysis software.

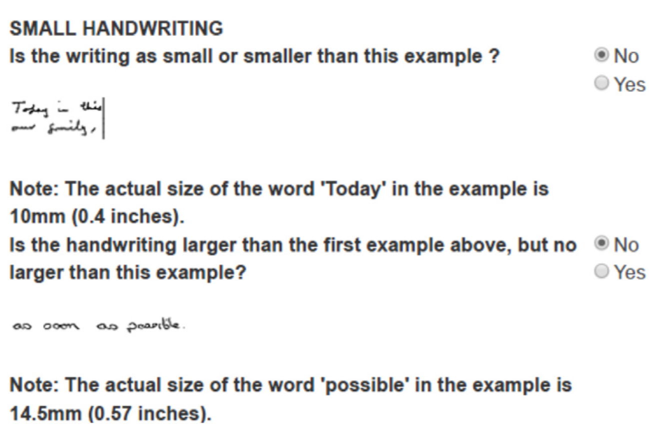

Fig. 5. Screenshot of graphonomizer handwriting analysis software.

factor are identified by a skilled graphologist, and are reduced to arrive at an optimal number of features that can be dealt with using any of the existing automated programs.

Open software programme like Handwriting Analyzer (www.sheilalowe.com), Graphonomizer (www.-garthmichaels.com), GraphoPro (www.graphopro.ch), or GRAF-2000 (www.graphologyinformationcenter.com) also exists. These are based on an embedded set of predetermined features and correlated personality traits.

In Fig. 5, researcher looks for the trait prompted by the software and provides binary input as 'yes' or 'no', based on the overall input the software provides a detailed report about the personality of the individual.

4.3. Data processing

As our study focuses on how to predict financial behavior using handwriting features, we have developed the features classification for each personality type (Fig. 3). Thus the personality and related financial behavior will be revealed by the baseline, connectedness, letter slant, margin, pen pressure, size of the letters and spacing. Table 4 illustrates specific handwriting features for individuals who are risk seekers, risk tolerant and risk averse.

From the literature review the following steps were gathered to apply machine learning technique to handwriting samples in order to classify into personality types (see Fig. 6).

4.3.1. Input-Scanned image of handwriting

Out of 200 handwritten specimens 112 scanned images were used for experimentation purpose. Each image contained a handwritten copy of the famous London Letter (as described earlier in Section 3.2.2). This text was cropped out manually and labeled manually through by graphologists in 23 distinct handwriting features. Out of these, 7 handwriting features were extracted based on the maximum occurrences of the particular trait in the sample and used to analyze if the financial behavior of an individual could be mapped as given in Table 4.

The images were further separated into different folders according to the given 7 labeled features. It was found that some handwritten sample images had two or more features e.g. ascending baselines and a rightward trend. Research studies found that training the system to read the traits before carrying out the actual analysis process with sample data will provide more accurate analysis (Abdul Rahiman M, 2013; Behnam Fallah, 2015). Accordingly, the system was trained in this study.

Table 4
Handwriting features for individual risk preferences.

Perceived financial behavior	Big five personality trait	Handwriting features
Risk seeker	Extraversion	• Wide spaced letters • Narrow right margin • Ascending baselines • Rather heavy pressure • Rightward trend • Connectedness • Irregular right margin
Risk tolerant	Openness to experience Conscientious	• Fullness (middle zone) • Good organization • Normal spacing between lines to broad spacing between lines • Connectedness • Released • Lower case 'f' and capital letter 'F' cuts at half • Middle size script • Even left margin
Risk aversion	Neuroticism Agreeableness	• Small size (middle zone) • T cross to right • Capital letter – Tall and narrow • Wide left margin • Legibility • Plain, unadorned, simple letter • Wide spaced letters

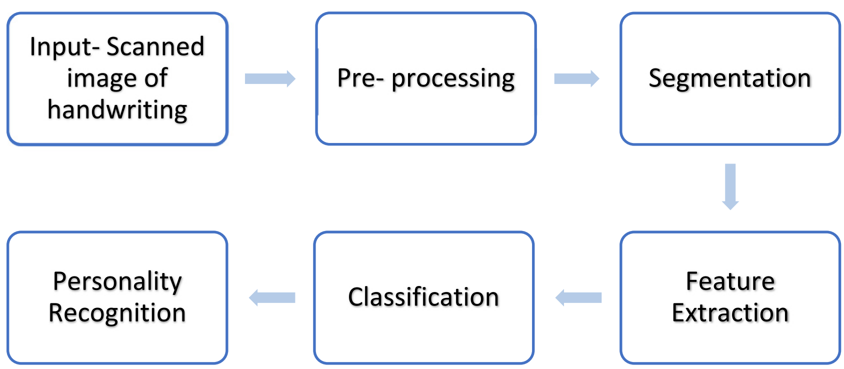

Fig. 6. Flow diagram of personality recognition system.

4.3.2. Pre-processing

Pre-processing included procedures to remove any impurities in the sample. Images were read using openCV[5] (cv2) and converted to grayscale. Every image can be represented using different methods for example RGB[6] and Grayscale (Intensity of Black color). For the purpose of analysis in this paper, the images were converted into Grayscale, with 256 possible intensities of black, where 0 = BLACK and 255 = WHITE. The data was subsequently normalized as follows:

i. Noise Reduction: Predominantly, Blurring and Non-Local Means Denoising Methods are used for noise reduction. We have used the Non-Local Means Denoising Method to completely remove any noise.
ii. Resizing: The images were resized into 2D array with each image being a 1024∗512 matrix of values, with each value ranging from 0 to 255. This produces a standard input size common across all images. 1024∗512 was chosen as it best fit the image dimensions of most of the London Letters samples.
iii. Thresholding: A model can become quite slow and overfitting if we use all the values from 0 to 255 for training. Hence, to improve the correctness of our model, we used global thresholding, i.e, we decided a cutoff pixel value of 220, above which the pixel value was changed to 255. Otherwise, the value was converted to 0.
iv. Erosion and Dilation: As we are using scanned images of handwritten text, some text tend to be less visible. Also, there can be some remaining noise still in the images. Hence, to overcome this problem, we first used erosion method, i.e, we removed the boundaries of the foreground object first and then dilated the image, i.e, increased the size of the foreground image. The combined process is called Opening (see Figs. 7 and 8).

4.3.3. Segmentation (separation)

Different research studies show that segmentation is of high importance to extract correct features. It helps to calculate the size of characters, for example, a risk tolerant individual should ideally have an optimal middle size script i.e. between 2.5 and 3.5 millimeters (Victor, 1952; McNichol, 2007). Segmentation can identify the correct size and use the same for personality identification from handwriting texts (Behnam Fallah, 2015; Abdul Rahiman M, 2013; Anthony Ma, 2017).

4.3.4. Feature extraction

Feature extraction process helps in extracting and reducing the features as given in Table 4 and thereby differentiate the handwritten text from one individual to another. This process includes extracting text independent features like margins, spacing

[5] OpenCV is a computer vision library in Python Programming Language.
[6] RGB—Red, Green, Blue.

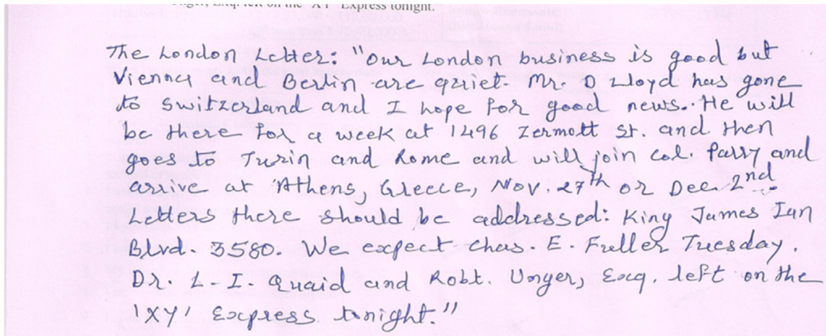

Fig. 7. Preprocessed handwriting sample.

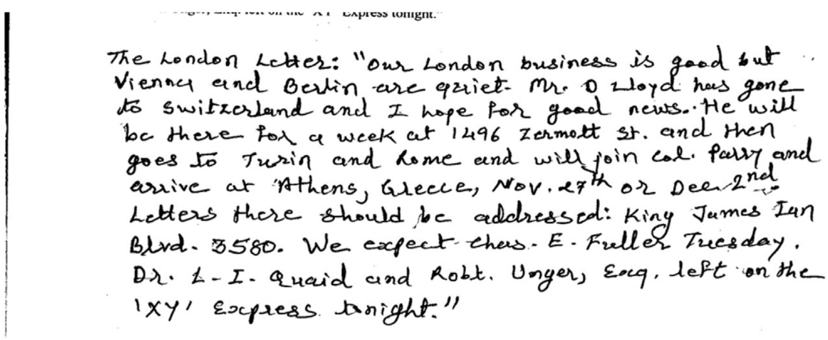

Fig. 8. Processed handwriting sample.

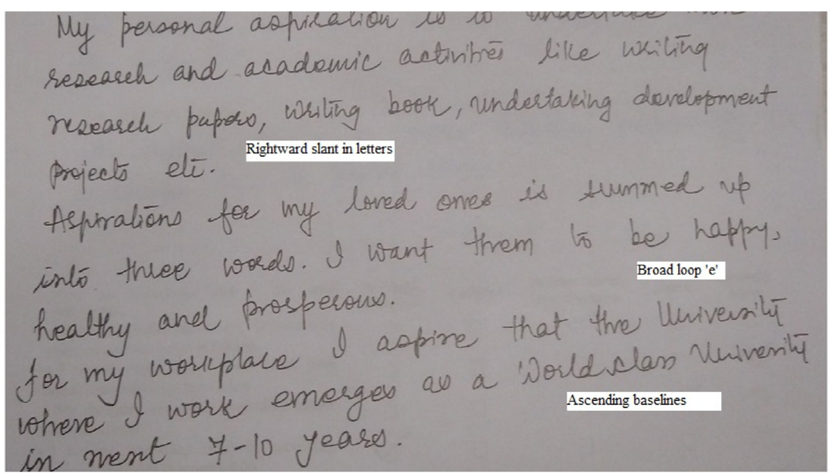

Fig. 9. Handwriting specimen of individual who may be risk seeker.

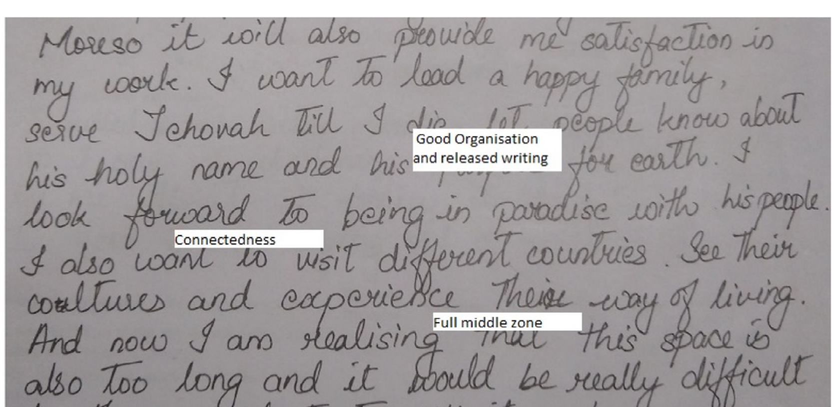

Fig. 10. Handwriting specimen of individual who may be risk tolerant.

between words and lines, slants etc. (Shitala Prasad, 2010; Abdul Rahiman M, 2013) (see Figs. 9 and 10).

For feature extraction the handwriting sample data set was divided as training data set and test data set in the ratio of 80:20.

4.3.5. Classification and recognition

A systematic study of the graphological features in the handwritten text of an individual would allow a graphologist to reasonably identify a writer's personality (Branston, 1998; Lazewnik, 1990). With the help of a graphologist, different handwriting features were identified and the feature vector matrices mapped to their corresponding classes (Prachi Joshi, 2015).

Studies have also been conducted using Feed Forward Network, which is an artificial neural network (ANN) wherein the connections do not form a fixed cycle. The information passes forward from input nodes to output nodes through any hidden nodes in only one direction. One of these studies used five handwriting features that are formations in letters 'i' and 'f', baseline slant, letter slant and pen pressure, to evaluate the baseline and pen pressure polygonization process and gray level threshold value was respectively used. The formations of letters 'i' and 'f' were analyzed using template matching. MATLAB was used to create the feed forward neural network and input values were given to ANN, as it is a supervised learning process the output was desirable (Parmeet Kaur Grewal, 2012; Anthony Ma, 2017) providing an accuracy of 97% and 99.1% from untrained writers and trained writers respectively (K Nithya Lakshmi, 2017)

To map the features extracted with the patterns that form the classification of the personality traits, we minimized the feature vector of each input pattern in proportion to one of the reference vectors (Abdul Rahiman M, 2013; Behnam Fallah, 2015; Prachi Joshi, 2015). When handwriting is represented mathematically in the form of feature vector it is known as feature vector matrix.

4.3.6. Neural network structure

The processed images of the handwritten text are passed into a Convolutional Neural Network (CNN). We chose CNN as herein capacity can be controlled by varying the depth and breadth, and they also make strong and correct assumptions about the nature of images (Alex Krizhevsky, 2017). Our CNN architecture starts with a Convolution layer, which uses a Kernel (matrix) to scan the entire image and generate a new set of data-points that are less dependent on the pixel values around any data point. Next, we passed this through a Max-Pool layer, which takes the maximum value around a pixel, essentially reducing our data size and extracting the essential features. The output is finally flattened to give a one dimensional array of elements, which can then be reduced to 7 neurons, representing the 7 classes we are trying to identify.

As discussed the data is split into 80:20 ratio, i.e, 89 samples for training and 23 samples for testing. The tuning of parameters in a Neural Network is called Training. The model learns about the features using the training dataset. The 23 samples, which the neural network model has not seen are then used to test the model. In testing, we check how accurate our neural network is based on data it has not seen before. The set of 89 samples is run through the model 20 times, i.e, 20 epochs. Neural Networks use Gradient Descent Algorithm (Y Lecun, 1998) to reach an optimal configuration which is a very slow algorithm and hence one iteration through the training dataset might not be enough to reach the optimal point. Hence, we use 20 epochs, where an epoch is one complete pass through the whole training set; it runs multiple iterations of gradient descent updates until you show all the data to the neural network, and then repeat the process.

The derived output array is passed through another Machine Learning Model called Logistic Regression. This is done because our Neural Network (NN) does not give us a binary value corresponding to the personality trait. It gives a value between 0 and 1, ex. 0.5674. But we need a binary value for our analysis. Hence, we trained our Logistic Regression Model with data output from the Neural Network and then tested our 23 samples. The structure of the neural net is represented in Fig. 11

4.4. Results

After training the model the training set was tested again on the model, wherein we got an accuracy of 97.27%, which denotes our training accuracy. This is good because a model should be very accurate with the data it has already seen.

We specify the results using 2 different tables for various attributes:

1. Confusion Matrix: It is one of the most preferred means of summarizing Classification based problems. It contains a table which tells us how many of the predicted values actually map to the real values. In our case, we have a binary output of 0 and 1. Hence the table shows True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). The positions are (1,1), (0, 0), (0,1) and (1, 0).

2. Classification Report: It is completely based on the Confusion Matrix. It comprises of:

a. Accuracy Score: Fraction of predictions the model got right.

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

b. Precision: Proportion of Positive identifications which were actually true.

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP})$$

c. Recall Score: Proportions of actual positives which were correctly identified.

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN})$$

d. F1 Score: It can be interpreted as a weighted average of precision and recall.

$$\text{F1-Score} = 2 * (\text{Precision} * \text{Recall})/(\text{Precision} + \text{Recall})$$

Wide space letters

Accuracy Score - 73.913% (∼74%)

Confusion Matrix -

	Predicted (0)	Predicted (1)
Actual (0)	0	6
Actual (1)	0	17

Classification report: -

	Precision	Recall	F1-Score	Support
0	0.00	0.00	0.00	6
1	0.74	1.00	0.85	17
Accuracy			0.74	23

Ascending baselines

Accuracy Score - 65.21% (∼65%)

Confusion Matrix -

	Predicted (0)	Predicted (1)
Actual (0)	5	1
Actual (1)	7	10

Classification report: -

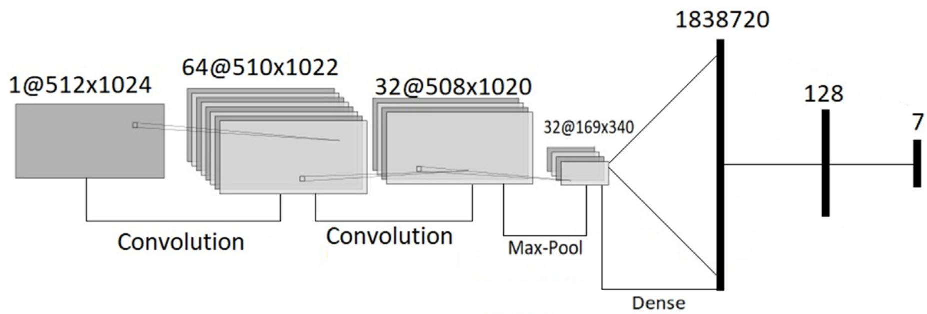

Fig. 11. Neural network structure.

	Precision	Recall	F1-Score	Support
0	0.42	0.83	0.56	6
1	0.91	0.59	0.71	17
Accuracy			0.65	23

4.5. Discussion

Use of machine learning showed that the training accuracy of handwriting samples was 97.27%, while the loss of data was 0.079. Further even a limited amount of testing data set, gave the test accuracy of 63.97% which is a positive sign towards further exploration of the use of the model. From the experimental study it was found that individual's high on extraversion score, exhibiting all the seven handwriting features of extraversion were more open to initiating new projects and believed in no risk no reward philosophy. Individuals with ascending baselines showed more tendency to buy products beyond their budget, while individuals whose handwriting features consisted of wide spaced letters and rightward trend appeared more interested in invesing in financial products like mutual funds. It was interesting to find that individual's with more than one type of outstanding loan[7] mapped at least four or more handwriting features out of the seven features related to extraversion. Thus, the experiment suggests that there is a positive relationship between taking risk and extraversion.

Apart from English, researchers have explored few writing systems like Chinese, Devanagari, Kannada, and Persian to understand the relationship between handwriting and personality. Although our experiment is based on English text insights into different scripts may be interesting to researchers. A study conducted by Wang et al. (2009) identified that character spacing in Chinese writing system has correlation with an individual's ability to reason and sensitivity (Tingting Wang, 2009). Another study on Chinese writing suggested that old age affects features like pen pressure, slant and tremor and distinguishing it from the handwriting of a young individual (Liu, 2011). Studies in Devanagari scripts have been able to achieve accuracy levels up to 99.12% on the test data using Library for Large Linear Classification (LIBLINEAR) and Multi-Layer Perceptron (MLP) (Halder Chayan, 2015). Authors using letter slant, size, margins and other letter arrangements like Sirorekha[8] concluded that disorientation in above features is likely to show writers disposition (Rajiv Kumar, 2017). The researchers working on writer identification from Kannada scripts extracted features from directional images as this script is generally curved in nature. The features of both vowels and consonants were analyzed using Multi-Layer Perceptron (MLP) with Back Propagation Neural Network (BPNN), accuracy levels were found to be 65% on test data (Ragha Leena, 2011). Sharif and Kabir's (2006) work is one of the earliest studies found for computer aided handwriting analysis in Persian script. The authors have extracted features based on margins, letter size, spacing and slant to support personality analysis along with expert graphologist opinions (Adnan Sharif, 2006). Similar approach to predict personality through handwriting features in Persian script was undertaken using support vector machine (SVM) on 120 samples (Somayeh Hashemi, 2015). The above studies suggest that using handwriting features to study personality and behavior can be applicable to writing scripts beyond English as well.

[7] Responses relating to outstanding loans like Education Loan, Housing Loan, Personal Loan, Vehicle Loan, Gold Loan and other interest payable loans was collected through questionnaire.

[8] Sirorekha (शिरोरेखा) is the upper line that links the letters and diacritics of a word in North Indic Brahmic scripts like Devanagari, Gurmukhi and Eastern Nagari.

4.6. Conclusion

Based on in-depth study of the literature and experimental method using Machine Learning we have developed the framework to classify the writer's personality using their handwriting features. With the use of machine learning methods it is possible to cross validate the data collected during the exploratory experiment and to evaluate that there is a potential to identify financial behavior using handwriting text features.

Research studies establishing linkages between handwriting analysis, personality traits and financial behavior can be of significant use to financial organizations. Implementation of the findings of this study can reduce the risks due to information asymmetry and moral hazard in financial markets. They can also support selling of financial products through identification of likely buyers. For example, financial advisors can help a 'neurotic' investor to make better investment choices, by designing their investment portfolio to suit their personality type. This research would contribute to the literature of a largely underexplored area; wherein handwriting analysis directly links personality traits with individual financial decisions.

CRediT authorship contribution statement

Sheetal Thomas: Conceptualization, Methodology, Investigation, Writing - original draft. **Mridula Goel:** Writing - review & editing, Supervision. **Dipak Agrawal:** Software.

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