Original Research Article

Evaluation of academic stress among medical students using graphology and machine learning algorithm in correlation with salivary cortisol

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ABSTRACT

Background: Stress is a part of the academic life of graduates. Young adults are especially susceptible to academic stress based on their subjective commitment towards academic goals, and social pressure for superior academic performance. Recognizing academic stress is crucial for planning successful management, and to prevent mental illness. The aim of the study was to develop methods to identify stress using graphology, machine learning algorithm and salivary cortisol.
Methods: The study included a mixed method research design and enrolled 43 medical students (19 males and 24 females) between 18-23 years of age were taken in the present study. The Kessler psychological distress scale (K10) was used to ascertain distress among the study subjects.
Results: Students written manuscript images were taken for artificial intelligence training and analysis. The written manuscript was evaluated for positive and negative personality traits using graphology techniques. One of the negative traits identified by graphology, i.e.; dejection, it was used to train a machine learning tool to identify the negative trait of dejection.
Conclusions: This study suggests that mental health professionals can train machine learning algorithms, using graphology tools, to function as a screening tool to determine stress levels. This may help to plan for management and recovery of stressed individuals and help them in future academic performance.

Keywords: Academics, Cortisol, Graphology, Machine learning, Mental health, Stress

INTRODUCTION

Medical education is a highly stressful course due to an extensive academic curriculum and affects the medical students' physical and mental health. High stress levels have a negative impact on cognitive functioning, appraisals and practical coping skills, and adaptive learning.[1] Effective recovery strategies and coping skills must manage stress. Coping is defined as 'constantly changing cognitive and behavioral efforts to manage

specific external and internal demands that are appraised as taxing or exceeding the resources of the person'.[2] 'Stress hormone', the cortisol used as a biomarker of psychosocial stress, can be used to assess biopsychosocial mechanisms triggered by the hypothalamus-pituitary-adrenal axis.[3] The hypothalamus triggers the hormone-corticotropin to release adrenocorticotropic hormone from the pituitary gland. In turn, this triggers cortisol release to the adrenal cortex.

Cortisol is released into the bloodstream and monitored by negative feedback by reducing CRH and ACTH secretion.[4] In central nervous system, cortisol, the steroid hormone, plays a crucial role in regulating cardiovascular activity, metabolism, brain and muscle energy, and the immune system. Almost all body tissues contain cortisol receptors.[5] Cortisol levels are highest in the blood, but cortisol also occurs in other fluids like saliva.[6] Samples of saliva were favored as a means for assessing cortisol as a valid stress biomarker. This matrix's choice is because there is a strong correlation between saliva and cortisol levels in the blood. Saliva cortisol is a good indicator of the body's biologically active substance. Further, saliva sampling is a non-invasive approach compared to blood sampling, which can be stressful to the patient and affect the outcomes.

Graphology, also known as handwriting analysis, is an art and science through which the formation of letters reveals the person's personality. Handwriting is also known as 'brainwriting' because the subconscious mind forms the characters, resulting in a habit. The subconscious mind sends electrical impulses to the hand resulting in the formation of the words. As we write, the subject internal feelings and emotions, which determine mood, will be recorded.

Graphology mainly measures our subconscious mind, which governs most of our attributes, behaviors, and coping efforts., This graphology idea is an expressive activity, a mixture of conscious thought and unconscious instinctual responses to impulses acquired in natural action. Research studies indicate that a thorough analysis of handwriting factors such as timing, fluidity, strain, scale accuracy, form, and the pace is a valid indicator of diagnosis of ailments and patient response to pharmacological therapeutic agents.[7]

Machine learning affects how we live and communicate with the environment, which will become more prevalent in the years to come. In our daily lives, machine learning can make a significant difference. As the modern technology pushing a second industrial revolution is more integrated with Artificial intelligence (AI) lives.[8]

Machine learning technology will improve work in many disciplines and provide new advances in Information and technology with a significant effect on our society. This AI technology may provide the means for engineering and biology to converge.[9] Hence, with this background,

and for the first time in India, machine learning-based graphology was implemented in a mixed-method study.

The objectives of this study were to evaluate academic stress among medical students using graphology variables; to evaluate academic stress among medical students using biochemical variables; and to develop and validate a machine learning algorithm for predicting and analyzing academic stress levels using graphology variables and biochemical variables.

METHODS

The study used a mixed-method design, prospective and cross-sectional study whereby 43 medical students (19 males and 24 females) volunteered as subjects, ranging from 18 to 26 years. Study was conducted in March 2019 at Akash Institute of Medical Sciences and Research Centre, Devanahalli, Bangalore. Ethical clearance was obtained from the Institutional Ethics Committee prior to the study. Informed consent was taken from subjects participated in this study. Subjects were assessed for salivary cortisol levels as stress parameter at two stages i.e. pre and post written examination. They were monitored to follow the protocol prior to the collection of salivary samples.

Medical students within the age group of 18-26 years, both male and female, willing to participate in the study and who has written minimum of 3 pages of answer script were included in this study. Those students suffering from illness or on medication for illness, non-medical students, written answer less than 3 pages scripts, not willing to participate were excluded from the study.

Protocol for collection of saliva

Subjects were instructed to refrain from eating, drinking, or brushing their teeth for at least 30 minutes before the test. Subjects were advised not to indulge in any strenuous physical activity, alcohol consumption, smoking, or caffeine from 7 pm the previous day up until the time of the study (intervention/control). They were instructed not to eat or drink anything except water for two hours before exposure to intervention/control measures. Each subject acted in his/her control. The intervention duration was 30-60 min (based on the time allotted for examination). Saliva samples were collected in controlled conditions subsequently two times (pre-test and post-test), a time period between 1:10 pm to 1:30 pm for pre-collection and 3 pm to 3:30 pm in post collection. The drool to collect saliva samples. 2 ml of saliva sample was collected and stored at -80°C until the analysis.

Sample preparation

The sample tubes were placed into a freezer and allowed to freeze. When ready to use, the samples were thawed to room temperature and centrifuged at 3000 rpm for 10 min to remove the particulate material. Then clear supernatants

were collected and transferred into freshly labeled tubes. All samples were tested in duplicate to minimize error that varied by more than 5% errors were repeat tested, and the average of the duplicates for each sample was used in the analysis.

Salivary cortisol

Salivary cortisol was estimated in pre-test and post-test salivary samples by the Competitive ELISA method (Diagnostic Biochem Canada Inc., CANADA) (Dirk, 2009).

Kessler psychological distress scale (K10)[10]

The K10 scale comprises 10 questions about emotional states, each with a five-level response scale. The questionnaire intended to yield a global measure of psychological distress based on questions about anxiety and depressive symptoms that a person has experienced in the most recent 4-weeks period. The responses to the items summed to produce a total score of psychological distress.
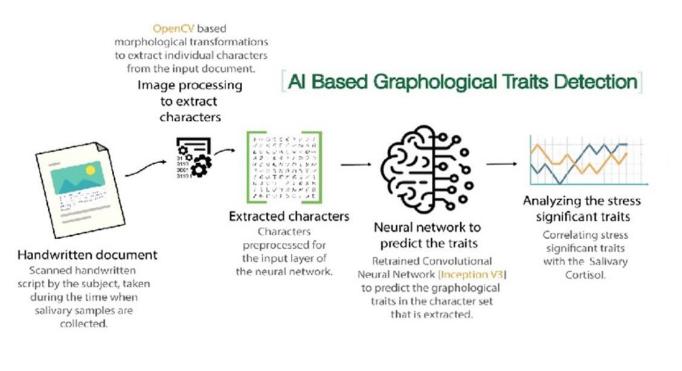
Graphology tools

Graphologists have developed an individual handwriting profile based on the theory of graphology, which incorporates analysis of handwriting uniqueness. The profile consisted of 30 features: text layout, boundaries, the direction of the line, line, spacing, letters and phrases, non-conventional letters, slanting of handwriting, handwriting deviation, letter size, a width of a letter, consistency and flux relation, writing speed, and expressive power.

Written exam text images were captured and used for graphology analysis. For every abnormal feature found within a participant's handwriting sample, 1 point granted, yielding a score ranging from 0 to 30. The characteristics (positive and negative) of each manuscript evaluated by using graphic techniques. These graphology features are used to train algorithms to classify negative features by machine learning.

Machine learning algorithm

In order to predict handwriting features from the written samples, morphological image processing operations were used to extract the image contours and separate individual letters in the document. This created a sub features set with the collection of individual handwritten alphabetical characters from the original document. The individual letters were processed with a pre-trained Convolutional Neural Network (CNN) to detect any graphology negative traits present in the subset of letters. Through this it was possible to detect any repetitive trait in the letters that might signify the graphological features.

The CNN model (Inception V3) with pre-trained weights was taken as a base model, in which the final classifier layers are retrained to detect the negative graphological traits. A dataset of around 1000 images per class was assessed by graphologist concurrently.

The graphological features from the handwritten document of each student involved in this study correlate to the stress amongst them. The overall results for the sum modules are presented in Figure 1.

Figure 1: Machine learning based graphological trait detection.

Statistical analysis

Statistical analysis was conducted using SPSS statistical program version 22 and R statistical tool. Relevant statistical packages were used to evaluate the study data for association, correlation and prediction.

RESULTS

Female students achieved higher grades than male students (p<0.05) (Table 1 and 2). Salivary cortisol levels were 27.39±7.86 ng/ml pre-test and 35.58±8.09 ng/ml post-test, which was statistically significant (p<0.001; Figure 2), implying that post-academic session stress levels were higher, and more so among female students.

Salivary cortisol levels decreased significantly at post-exam for students with pre-test salivary cortisol levels greater than 30 ng/ml, compared to those with less than 30 ng/ml (Figure 3).

Table 1 demonstrates a statistically significant gender difference in academic performance. Table 2 demonstrates a statistically significant gender difference in academic distinction. Table 3 shows a significant correlation between Dejection based on machine learning (DML) and Dejection based on graphology (DG).

A significant difference in pre- and post-interventional salivary cortisol levels was observed, as illustrated in Figure 2. Figure 3 depicts a significant difference in salivary cortisol levels between pretest and posttest samples vs pretest salivary cortisol values.

In Figure 4, a significant difference was observed between minimal and maximum distress using the K10 versus the difference in post-pretest cortisol (biological stress) levels. The median cortisol salivary post-preexamination was 12.3 ng/ml between minimal distress and maximum distress categorized using the self-reported distress K10 scale (Figure 4).

K10 self-reported cortisol distress score with pre-post cortisol levels categories as 0: no distress- 1.75 ng/ml; 1: middle distress- 5.0 ng/ ml; 2: moderate- 12.5 ng/ml with a statistically significant difference was observed (p<0.001) by statistical analysis. The pattern of females' Graphology negative trait scores is depicted in Figure 5.

Machine learning chart of graphology negative traits was significantly higher in the post-test period than in the pre-test period, and the correlation between these traits and biological stress as measured by salivary cortisol was significantly higher in the post-test period than in the pre-test period (Figure 6).

Table 1: Academic performance of female and male subjects.

Parameters	Median (Q1, Q3)		W value	P value
Gender	Female (N=24)	Male (N=19)		
Academic ranks	21 (16, 24)	18 (15,22)	322.5	<0.05*

Note: *Statistically significant difference; W value-Kendall's W statistic.
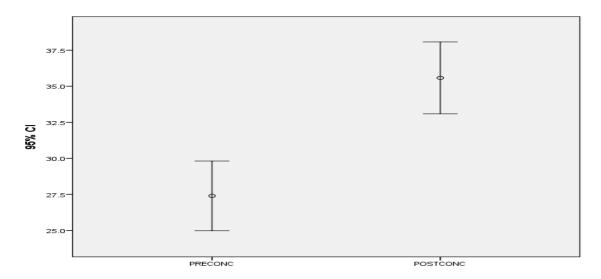
Table 2: Academic distinction among the study subjects.

Subjects		Academic distinction			Chi square value	P value
		No (%)	Yes (%)	Total (%)		
Gender	Female	9 (37.5)	15 (62.5)	24 (100)		
	Male	14 (73.7)	5 (26.3)	19 (100)	4.22	<0.05*
	Total	23 (53.5)	20 (46.5)	43 (100)		

Table 3: Correlation of Dejection based on machine learning (DML) and Dejection based on graphology (DG).

Correlation			DML	DG
DML	Correlation coefficient		1.000	0.428
	P value		-	0.004*
	N		43	43
DG	Correlation coefficient		0.428	1.000
	P value		0.004*	-
	N		43	43

Note: *Statistically significant difference; DML- Dejection based on machine learning; DG- Dejection based on graphology.

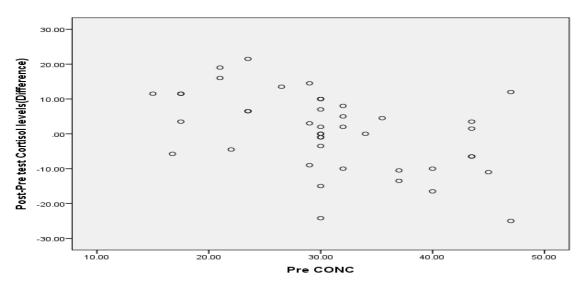**Figure 2: Pre and post interventional salivary cortisol levels.**

Figure 3: Difference of salivary cortisol levels between post-test and pre-test samples verses pre-test salivary cortisol values.
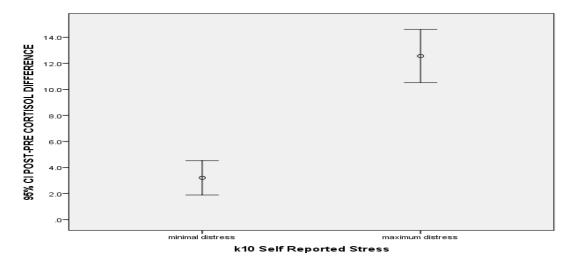

Figure 4: Difference of salivary cortisol levels between post-test and pre-test samples verses pre-test salivary cortisol values.
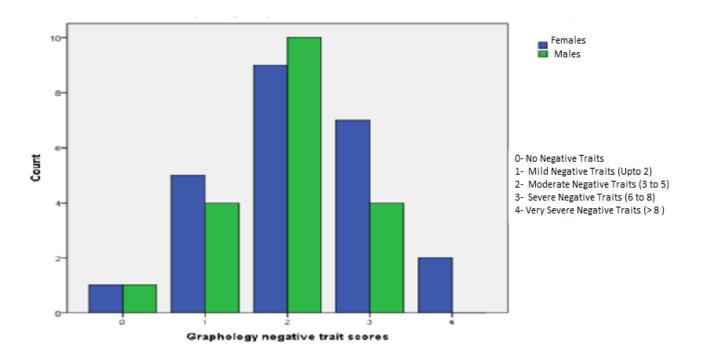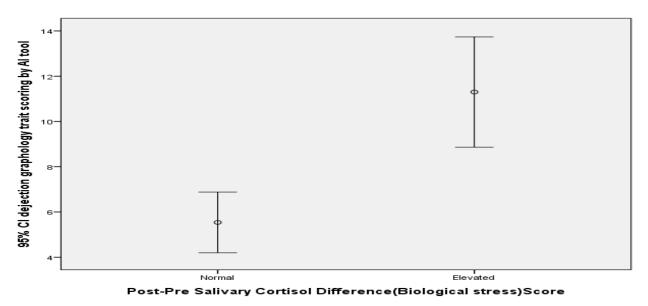
Figure 5: Distribution of graphology negative trait scores among male and female subjects.

Figure 6: Machine learning charting of graphology traits and correlation with biological stress using salivary cortisol.

DISCUSSION

In the current study, we discovered that chronically distressed students had a decreased HPA axis activity compared to those without chronic distress. According to Singh et al, chronically stressed students displayed decreased HPA axis activity compared with the normal students as seen in (Figure 3).[11] This means that the HPA axis is reduced due to chronic distress activity commonly seen by patients prone with chronic depression and chronic anxiety. A strong association was been found between stress and student academic outcomes in the present study.[12] This is consistent with a study led by Chada et al in which the stress level of pharmaceutical students has been associated with their stress perceptions and performance.[6] The university exams are one of the most severe pressures perceived by students seen in current study as well.[13] Other research studies, have found not much relation found between the levels of cortisol and perceived stress. In contrast, Ebrecht found that perceived stress and cortisol levels had no association.[14] In a study of

the cortisol level of dental students, Ng et al showed that cortisol increased dramatically during acute exam stress studies.[15] Regardless, many studies showings statistically significantly increased salivary cortisol levels post-examinations thereby suggest that analyzing stress in pre-examination studies is important and essential in understanding stress response.

Graphology is an old discipline in China that has been developed to examine individuals' personality and actions through physical characteristics and manual writing patterns.[16] In 1942 L-Z scales were developed by T. S. Lewiston and J. Zubin, graphologist and psychologist, in order to empirically test quantitative and qualitative handwriting components.[17] The resultant scales helped expert graphologists in various languages to recognize relevant handwriting features and how they interact. Broad or absolute conclusions could not be drawn based on a single feature alone. The combination of various features that interacted in different ways facilitated a more easily interpretable system for clinicians and also used in criminal trials and investigations. Handwriting is a recognized medical health method to treat attempts at suicide and extreme major depressive disorder.[18] Graphology negative traits found in this study were dejection (13%), gullibility (13%), procrastination (55%), sensitivity to criticism (52%) and selective listening (63%). Out of these many negative traits dejection was considered for correlation with salivary cortisol and for training a machine learning algorithm. Negative graphology traits score were moderate in both male and female subjects, with average scores of 3 to 5. However, severe and very severe negative traits of 6 to 8 and >8 were only observed among female subjects (Figure 5).

New endeavors, i.e.; machine learning, are important and beneficial for graphologists and psychologists in a number of areas within the field of mental health. In order to provide a solution or response to a question, machine learning uses a variety of different algorithms, decision-taking capabilities and a large amount of data.[19] In the present study, a machine learning algorithm was trained in the analysis of graphology traits, students with elevated cortisol salivary levels showed increased negative graphological characteristics using machine learning algorithms. Students with lower marks showed a significantly higher score for graphology negative traits. In this study, correlation of DML and dejection based on DG were found to be moderately correlated and statistically significant (p<0.05) (Table 2). However, further extensive and elaborative studies are required to validate the results of this study.

Limitations

A small group of medical students was sampled, which might reduce the ability to generalize to a broader population. However, the study sample did include healthy individuals which reduced the influence of confounding factors. Further, the sample study also had statistical power to detect effects.

The study consisted of a heterogeneous group comprising of both genders instead of a homogenous group of just males or females. The study involved a single graphologist, only one negative trait of dejection. However, future studies may expand on this to a machine learning tool to detect more negative traits. A large population study with multiple blinded graphologists are required to corroborate our findings. Only the K10 stress questionnaire was used to measure psychological distress. A specific perceived stress scale could be used in future studies among students. Further, the Study did not include any examination of methods to help recovery to stress reactions. A future study may explore this.

Future scope

In future studies, similar graphology analysis using machine learning protocol could be used to determine whether this approach analysis could be used as an objective method to detect other mental health disorders, including major depression, and, thus, whether it would be useful in its early diagnosis to clinicians. These advances in autonomous decisions and algorithm learning can be used to remove human prejudices from critical tasks. Machine learning can thus act as a bridge between current mental health, graphology and academic know-how. This may lead to improved detection of casernes, major improvements in medical professional's education programs. This study suggests that professionals in mental health care can use machine learning algorithms and graphological methods as a screening tool to determine academic stress levels among medical students

CONCLUSION

These advances in autonomous decisions and algorithm learning are used to remove human prejudices from critical tasks. In future studies, similar graphology analysis using machine learning protocol could be used for an objective method to detect other mental health disorders, including major depression, thus, help in early diagnosis to clinicians. Machine learning can thus act as a bridge between current mental health, graphology, and academic know-how. This may lead to improved detection of mental illness and significant improvements in medical professionals' education programs. This study suggests that professionals in mental health care can use machine learning algorithms and graphological methods as a screening tool to determine academic stress levels among medical students.

ACKNOWLEDGEMENTS

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