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AI-Enhanced GraphoText Analysis for Tracking Counselling Therapy Progress: Integrating Multimodal Graphology and Machine Learning

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ABSTRACT

Despite the robustness of existing instruments, routine manual observation in psychotherapy faces significant challenges, including lack of time, labour, high implementation costs, and potential biases such as response bias and social desirability. This study proposes a dynamic assessment approach using machine learning and multimodal features extracted from handwriting, incorporating graphology-based and content-based features. The integration of content-based and graphology-based features involves combining text and handwriting features with the Support Vector Machine (SVM) using the Radial Basis Function Kernel (RBF). The results show that this approach achieves an impressive accuracy rate of 86.25%. The proposed framework not only improves psychotherapeutic practise, but also offers new insights into human cognition and emotional dynamics by revealing intricate patterns in handwriting. This advance facilitates data-driven decision-making, improves the quality of patient care, and overcomes challenges associated with manual monitoring, including social desirability bias and response set bias. This research paves the way for innovative methods at the interface of mental health and technology, and promises a more objective and efficient approach to monitoring the progress of psychotherapy.

Keywords:

Multimodal-graphology; Machine learning; Content-based; AI

1. Introduction

Psychotherapy is a well-known and effective treatment process in the psychology domain to facilitate in adjusting one’s thoughts, feelings, and behaviour. Psychotherapy has been beneficial across age cohorts, gender, and culture to overcome different issues in mental and behavioural health (Lambert, Bergin, and Garfield 1994) [1]. Research have proved that different psychotherapy techniques contribute to a substantial effect in addressing specific issues in psychological and behavioural health. For instance, cognitive-behavioural therapy (CBT) is effective in treating insomnia [2], internet gaming disorder [3,4], obsessive-compulsive disorder [5], gambling disorder [4], and eating disorder [6]. Interpersonal psychotherapy (IPT) is an effective treatment for postpartum

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depression and anxiety [7], post-traumatic stress disorder (PTSD) [8], and depression for pre-adolescents [9].

Technological advancements have shifted the norms of traditional settings in every sector, including mental healthcare [10]. For instance, mobile psychotherapy games have been utilized for the elderly with memory disorders [11], and image-based virtual reality has been useful for self-therapy to reduce stress [12]. When the COVID-19 pandemic hit populations worldwide, the cases of mental healthcare increased tremendously. This led to rapid changes in the landscape of counselling practices, adopting digital counselling to handle mental health issues. The effect of the pandemic causes the growth of digital counselling to be adopted rapidly [13]. Studies have demonstrated that digital counselling e.g., text-based cognitive behavioural therapy (CBT) treatment brought a significant positive impact on the counselling domain [2,14]. The disinhibition effect of digital counselling causes the clients to be more open and natural when consulting with the counsellor during the therapy session. The text-based emotion expressed during the therapy could be used to frame one's progress monitoring. Machine learning and deep learning have empowered algorithms in enabling models to process, analyse data, and extract patterns in digital healthcare. It holds promises for complementing limitations in health care. For instance, research has explored machine learning in detecting diabetic retinopathy [15], predicting disease outbreak [16] detecting depression [17], and predicting symptoms of depression in cancer treatment [18]. Apart from the aforementioned domains, the psychology or counselling domain also leverage deep learning and machine learning in monitoring the progress of psychotherapy sessions. These includes verbal assessment and counselling [19], monitoring routine outcome in psychotherapy [20], recognize emotion through face recognition in psychological intervention system [21], and identifying evidence-based psychotherapy outcomes for post-traumatic stress disorder [22].

Routine outcome monitoring is important to assess the efficacy of psychotherapy treatment. Current practices in monitoring psychotherapy progress are mainly based on behavioural coding and routine outcome monitoring instruments. Many instruments have been introduced, e.g., Outcome Questionnaire System (OQ-45), the Clinical Outcomes in Routine Evaluation (CORE) and the Partners for Change System (PCOMS) [23]. While the current instruments used are robust, the manual monitoring practice faces a few challenges. Apart from time constraints [20], manual monitoring instruments are labour intensive and expensive to implement. It could also lead to response set biases, social desirability biases, and psychometric limitations.

Therefore, the intervention of an automated approach using artificial intelligence (AI) techniques could be implemented to assist in monitoring the progress of a patient during psychotherapy treatment to assess the quality and outcomes of treatment. The AI-based monitoring tool is potentially needed to complement and enhance the process of treatment monitoring. This paper aims to present an AI-based monitoring framework for analysing the counselling therapy session throughout treatment using machine learning approach. An AI- based analysis could help to measure and analyse a client's treatment outcome by tracking the client's current and recurrent views of sentiment and emotion.

Handwriting has substantial beneficial effects in many applications. The handwriting was used to assess the fine-motor control skills, kinaesthesia, and sensory awareness in children [24]. For neuropsychological assessments, studies have used handwriting to determine the presence of brain dysfunction. Parkinsonism symptoms were identified through sequential-based dynamic handwriting analysis [25,26]. Early diagnosis and monitoring of neurodegenerative diseases were also reported using handwriting analysis, e.g., Alzheimer's diagnosis [27,28]. Handwriting has also been presented in research to determine one's personality [29-31], learning style [32], in forensic [30,33], as well as age detection [34]. Apart from handwriting, other studies have explored content- based to predict the client-rated therapeutic alliance [35]. Other work used topic models with linguistic data i.e., psychotherapy textual data to identify the clients' functioning levels and alliance ruptures in psychotherapy [36]. While some studies, such as Ewbank *et al.,* [37], have utilized topic models with linguistic data to identify clients' functioning levels and alliance ruptures in psychotherapy, others like Goldberg *et al.,* [38] have focused on predicting therapeutic alliance using linguistic content from therapy sessions. Various machine-learning approaches have been used in handwriting analysis. For instance, Support Vector Machine (SVM) [29,31], topic model [36], deep learning [14,37], Artificial Neural Network (ANN) [39,40], least square linear regression and rule-based algorithms [30], and multi-classifiers [27]. However, to our knowledge, no study has addressed the multi-modal features of handwriting.

The current state of psychotherapy emphasizes the value of routine outcome monitoring as a tool for assessing treatment efficacy. However, the current methodologies primarily rely on behavioural coding and routine outcome monitoring instruments, which highlights a noticeable gap in real-time progress assessment. In contrast to the prevalent post-session evaluation approach, which offers insights only after the session's completion, there is a compelling need to shift towards immediate progress monitoring following each therapy session. The incorporation of immediate progress monitoring can play a crucial role in detecting any deviations within ongoing psychotherapy sessions and thereby enable timely adjustments to the treatment plan. Addressing this gap, the study aims to develop a machine learning-based framework for monitoring the progress of psychotherapy sessions using multi-modal features extracted from one's handwriting i.e., graphology-based features and content-based features. The objective is to introduce a dynamic assessment approach that captures session outcomes as they unfold, in stark comparison to the prevalent retrospective analysis method. In this way, it could facilitate the effectiveness and efficiency of monitoring treatment progress which potentially further improved the outcomes of therapy.

2. Methodology

2.1 AI-Enhanced GraphoText: The Holistic Digital Monitoring Framework

The proposed GraphoText framework for digital psychotherapy monitoring is illustrated in Figure 1. GraphoText is a holistic framework integrating the four (4) major phases from data acquisition to data visualization. The initial phase (data acquisition) of this framework is the process of acquiring handwriting from a client during each therapy session. The client will require to write whatever comes to their thought without dictating i.e. free flow writing. During the feature extraction phase, the model will extract two (2) types of features from a piece of handwriting i.e.

i. graphology-based features
ii. content-based features.

For graphology-based features, there are two (2) specific features will be extracted, which include baseline and slanting. Whereas the content-based features will be focused specifically on the Term frequency-inverse document frequency (TF/IDF), sentiment, keyword, and absolute words. The collection of extracted features will be stored in the client's monitoring record database. Then, the classification model will be performed using the machine learning approach.

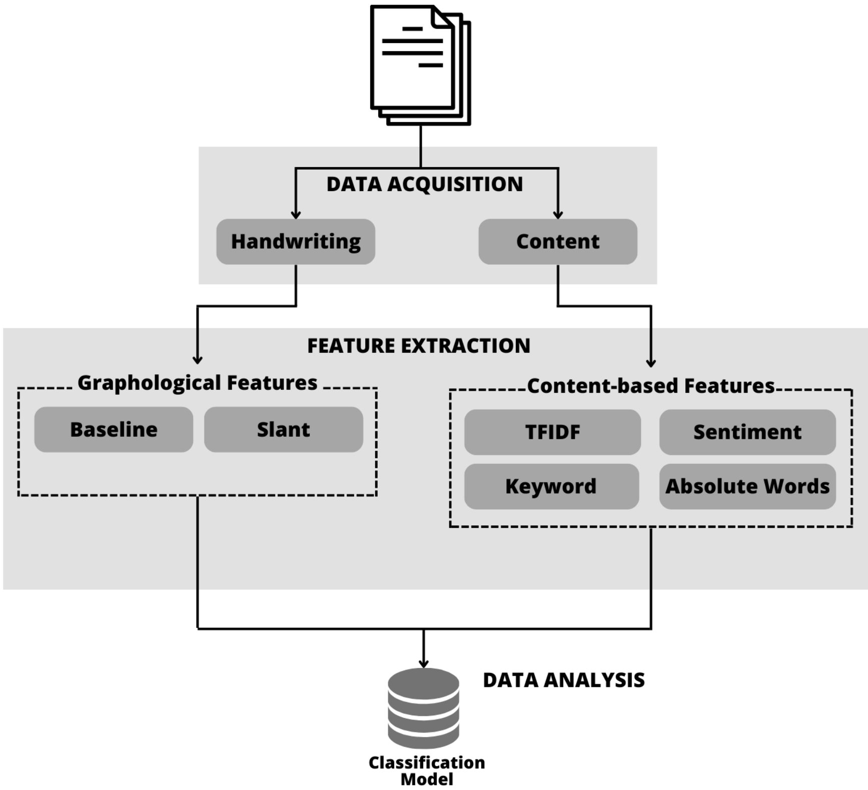

Fig. 1. AI-Enhanced GraphoText: the holistic digital monitoring framework

2.1.1 Dataset

In this experiment, we utilised a dataset which was extracted from a real-world handwritten text sample. We employed Malaysian adults with an age range spanning from 20 to 60 years. Each participant was provided a blank A4 sheet, granting them the freedom to transcribe their unfiltered thoughts, whether in Malay or English, in accordance with their preferences. In order to comprehensively assess the participants' distinctiveness, a supplementary questionnaire was administered, aimed at evaluating the five discrete personality dimensions delineated within the Big Five Inventory-10 (BFI-10) [25]. This comprehensive approach aimed not only to capture their handwriting attributes but also the nuanced facets of their personality traits.

However, during the preprocessing phase, 30 sets of samples were excluded due to a range of factors including incomplete personality scores, missing handwriting content (blank submissions), and instances where only signatures were provided. As a result, the final dataset comprises a compilation of 70 handwritten images, each originating from separate individuals. This compilation effectively captures the synthesis of their distinct writing styles and individual personality traits.

2.2 Multi-Modal Feature Extraction
2.2.1 Graphology-based features

Handwriting carries a unique and exclusive non-verbal expression of the writer. One's mental and psychological state could reveal through strokes and patterns in handwriting. Previous study by Abd Yusof *et al.,* [42] found that graphology analysis is useful in identifying a writer's personality traits. Based on the previous finding [42] this framework proposed to focuses on three (3) graphological features:

i. baseline
ii. slanting
iii. whitespace

Baseline is one's handwriting in the flow of writing either straight, ascending or descending. A straight baseline signifies that an individual displays steady and externally organized conduct, while also being practical, meticulous, and controlled. An increasing baseline portrays the person as optimistic, joyful, engaged, and energetic. Furthermore, it signifies their inclination to remain consistently occupied and active. In contrast to ascending baseline, a descending suggests that an individual is negative in outlook, going through temporary mental fatigue, and encountering digestive problems. The tilt of the handwriting is determined by the angle of inclination and the direction of the letters, as well as the angle formed between the letter's downstroke and the baseline. This slant conveys information about the writer's emotions, level of sentiment control, and emotional regulation. Rightward slant is when the words leaning towards the right. Whereas leftward slant is when the words leaning towards left. For instance, as shown in Figure 2, the baseline is the straight, and; leftward slant. Each parameter in handwriting carries a different meaning and analysis. Together baseline and slant represent the emotional stability of the writer.

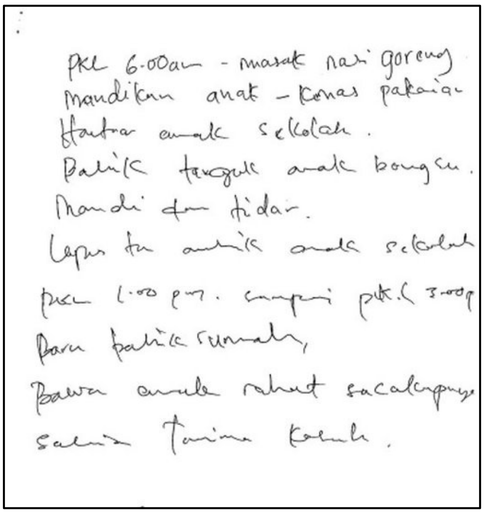

Fig. 2. An example of handwriting for graphology analysis used in previous study [39]

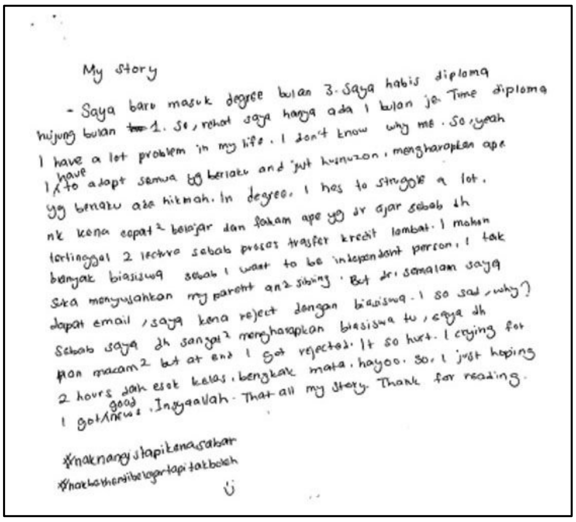

Fig. 3. An example of handwriting for content analysis used in previous study [39]

Table 1 summarizes the graphology-based features used in this study.

Table 1
Summary of grapho-based features used in this study

Feature	Description
Baseline	0, if baseline is straight
	1, if baseline is ascending
	2, if baseline is descending
Slant	1, if rightward slant
	2, if leftward slant

2.2.2 Content-based features

Content analysis generally is the process of understanding the meaning of and in texts, which includes the development of categories from the data. It has been widely used in marketing and consumer behaviours [43], mental healthcare [44,45] etc. The content analysis focuses on the content itself. For instance, as shown in Figure 3, the content is "*.... Saya baru masuk degree bulan 3. Saya habis diploma hujung bulan 1. So rehat saya hanya ada 1 bulan je. Time diploma i have a lot problem in my life. I don't know why me? So yeah i have to adapt semua yang berlaku and just husnuzon, mengharapkan apa yang berlaku ada hikmah. In degree i have to struggle a lot*". The analysis of this content will be based on the relevance/importance of specific keywords and with the nuances of the document on the depression perspectives as in previous study [41]. Four (4) main features have been considered in content analysis:

i. (TF/IDF)
ii. Sentiment
iii. keyword
iv. absolute words

TFIDF is a vector that assesses the significance of a word within the context of the entire document. It is then vectorized to effectively reduce feature dimensions and emphasize the word's importance in relation to the rest of the content. Sentiment, keywords, and absolute words are all related to sentiment-expressing words, words associated with depression, and the connotation of words within the document. In this study, we utilized the VADER (Valence Aware Dictionary for Sentiment Reasoning) lexicon to analyse sentiment, categorizing it into two (2) categories: positive/neutral and negative sentiment. Depression-related keywords are divided into six categories:

i. emotions
ii. feelings
iii. depression
iv. issues related to depression
v. absolutism
vi. point of view

Absolute words are those that convey totality, such as "*entirely*" "*always*" "*totally*" and "*never*". In this study, we considered at least three (3) token matches for keywords in the lexicon and an absolutist index greater than 1.1%. Table 2 summarizes the content-based features used in this study.

Table 2
Summary of content-based features used in this study

Feature	Description
TF-IDF	Range between 0 to 1. Higher value means higher frequencies
Keywords	0, if token matches for keywords in the lexicon < 3
	1, if token matches for keywords in the lexicon >= 3
Sentiment	0, if sentiment is positive or neutral
	1, if sentiment if negative
Absolute words	True, if absolutist index greater than 1.1%.
	False, if absolutist index lower than 1.1%

2.2.3 Integration of content-based and graphology-based features

The integration of content-based and graphology-based features involves combining textual and handwriting characteristics to create a comprehensive analysis approach that captures both linguistic and behavioural aspects for enhanced understanding and interpretation. By training the machine learning models on a diverse dataset containing samples of both written content and corresponding graphological features, the system learns to recognize intricate correlations that might not be easily discernible through manual analysis alone. This integrated approach not only enhances the accuracy of interpreting psychological and emotional traits but also provides a more comprehensive and automated means of monitoring counselling therapy progress.

We utilized the Support Vector machine (SVM) with Radial Basis Function Kernel (RBF) kernel. RBF employs a sequential composition of multiple polynomial kernels, each with varying degrees, to facilitate the transformation of non-linearly separable data into a higher-dimensional space. This transformation enabling the separation of non-linearly separable classes through the use of hyperplanes. The process involves mapping the dataset into this augmented space by calculating dot products and squaring all features. The RBF kernel function in Eq. (1) can be described as

$$K\ (X_1, X_2) = exp(-\gamma\ ||\ X_1 - X_2||^2) \tag{1}$$

The kernel function's output K is to measure how similar or dissimilar the two input data points X_1 and X_2 are in the feature space. Where, it calculates the similarity between two input data points X_1 and X_2 in a multidimensional space, by computing the exponential of the negative squared Euclidean distance between them, scaled by the gamma γ parameter value ranges from 0 to 1.

For the performance metrics, we use accuracy, precision and recall as shown in Eq. (2), Eq. (3), and Eq. (4). The accuracy is used to evaluate the model's overall performance, while precision and recall metrics provide insights into its ability to minimize false positives and effectively capture true positive instances, respectively.

$$Accuracy = \frac{Total\ number\ of\ corrected\ predictions}{Total\ number\ of\ predictions} \tag{2}$$

$$Precision = \frac{True\ positive}{True\ positive + False\ Positive} \tag{3}$$

$$Recall = \frac{True\ positive}{True\ positive + False\ Negative} \tag{4}$$

3. Results and Discussion

3.1 Prediction Outcomes

Table 3 compare the performance metrics (accuracy, precision, and recall) of three different models based on the features used:

i. content-based
ii. grapho-based
iii. a combination of both.

The content-based features model achieved high recall (1.00), indicating that it effectively captured all emotionally unstable cases. However, its precision (0.75) suggests that some emotionally stable cases may have been incorrectly classified as unstable. The accuracy of this model (75.0%) reflects the overall correctness of predictions. In contrast, the grapho-based features model demonstrated a balance between precision and recall, with a slightly lower precision (0.63) but a higher recall (0.82) compared to the content-based model. The accuracy (80.0%) indicates a satisfactory overall performance.

Notably, the integration of content-based and graphology-based features using the SVM-RBF classifier yielded the highest accuracy rate of 86.25%, with a notable increase in precision (0.87) compared to the individual models. However, the recall (0.65) decreased, suggesting that some emotionally unstable cases may have been missed. This finding underscores the model's pronounced ability to achieve accurate predictions, particularly in tracking the emotional stability of a writer. This holistic approach allows for a more accurate representation of emotional states and tendencies, enabling precise predictions with minimal margin for error.

Moreover, the precision value of 0.87 reflects the model's ability to discern true positive instances from false positives, indicating its reliability in identifying emotional stability with high confidence. This precision is crucial, especially in sensitive domains such as psychological profiling, where accuracy is important for informed decision-making and intervention. Additionally, the recall value of 0.65 (also referred to as sensitivity), provides insight into the model's capacity to correctly identify positive instances within the entire dataset of actual positive instances. This metric demonstrates the model's sensitivity to emotional cues and signals, ensuring that no relevant information is overlooked or disregarded during the assessment process.

Overall, the results presented in Table 3 highlight the robustness and efficacy of the transformative advancements in data driven approaches to emotional assessment. They showcase the model’s potential for practical application in various domains, such as psychological profiling and personality assessment. This comprehensive evaluation not only underscores the model's performance but also underscores its utility and adaptability across different contexts, emphasizing its relevance and significance in contemporary data analysis and interpretation. However, it is important to explore that there is a trade-off between precision and recall, highlighting the importance of considering the specific requirements and objectives of the predictive model when selecting features.

Table 3
The result of three (3) different classification model based on SVM-RBF classifier

Model	Accuracy	Precision	Recall
Content-based features	75.0%	0.75	1.00
Grapho-based features	80.0%	0.63	0.82
Content + Grapho-based features	86.25%	0.87	0.65

3.2 Confusion Matrix Analysis

The confusion matrix in Table 4 demonstrates how the model classifying the predictions into different categories. In this study, we focus on the model’s ability to predict emotionally unstable cases. The matrix highlights that out of the total emotionally unstable cases, the model successfully predicted 55, indicating a strong performance in identifying handwriting patterns associated with emotional vulnerability. However, it's crucial to acknowledge that there were instances where predictions were inaccurate, which highlight areas for potential improvement and underscore the task's complexity.

Table 4
Confusion Matrix for Content + Grapho-based features with 10-fold cross validation

N=80	Actual emotionally not stable	Actual emotionally stable
Predicted emotionally not stable	55	8
Predicted emotionally stable	3	14

Based on observations showing lower performance in the content-based model compared to the grapho-based model, we suggest that these mismatches may have occurred due to language barriers. The sentiment and depression-related keyword dictionary may not have comprehensively covered the Malay language, potentially leading to misclassifications in emotionally stable and unstable cases. This gap risk losing valuable insights, as the uncovered Malay words may carry significant meaning regarding the writer's emotional state.

Thus, we propose further exploration of an improved Malay dictionary for sentiment, depression-related keywords and absolute words to refine the dictionary and cater to the art of the Malay language. This exploration involves expanding the existing dictionary to include culturally relevant terms and expressions commonly used in Malay-speaking communities to describe emotions, mental health issues, and related concepts. By incorporating these insights and continuously refining the dictionary, we can enhance its accuracy and effectiveness in detecting and understanding depression-related language cues in Malay text. This effort not only contributes to improving the performance of natural language processing tools and models for mental health assessment but also promotes culturally sensitive and inclusive approaches to addressing mental health challenges in Malay-speaking populations.

In summary, the results highlight that the integration of content-based and graphology-based features, coupled with the SVM-RBF classifier, contributes to a robust predictive performance. The model not only excels in accuracy but also demonstrates commendable precision and recall values, collectively signifying its competence in accurately identifying emotional states based on handwriting features.

4. Conclusions

This research represents a significant step in enhancing the objectivity and effectiveness of psychotherapy through the integration of machine learning and multi-modal handwriting analysis. The study successfully demonstrates that by extracting various features from participants' handwriting, it is possible to monitor the progress of psychotherapy sessions with a high degree of accuracy. This objective approach surpasses traditional subjective assessment methods, offering a promising tool for evaluating psychological well-being and therapeutic advancement. The implications of this research are far-reaching.

Beyond monitoring therapy progress, this framework creates a bridge between psychological analysis and machine learning, opening the door to more precise mental health evaluation methods. The success of this approach highlights the untapped potential of seemingly simple handwriting features in uncovering complex cognitive and emotional transformations. However, there are limitations to consider. The sample size and diversity of participants may affect the generalizability of the findings. Additionally, ethical considerations, such as data privacy and informed consent, must be addressed for real-world applications.

In conclusion, this research marks a significant advancement in objective progress monitoring in psychotherapy, with the potential to improve the practice of therapy and deepen our understanding of human cognition and emotions. It offers data-driven insights that can enhance decision-making and patient care while overcoming biases associated with manual monitoring. As the field evolves, this study sets the stage for further exploration, refinement, and application of innovative methodologies at the intersection of mental health and technology.

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