Accessing Trust in Mental Health Counselling Conversation

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THESIS CERTIFICATE

This is to certify that the thesis titled **LaTeX CLASS FOR DISSERTATIONS SUBMITTED TO IIT-M**, submitted by **Author**, to the Indian Institute of Technology, Madras, for the award of the degree of **Doctor of Philosophy**, is a bona fide record of the research work done by him under our supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

KEYWORDS: Trust ; Mental Health ; Dialogue Systems ; Time-Series Modelling

Mental health has emerged as the most critical global healthcare concern which is accelerated by recent lifestyle changes, evolving individual aspirations, and social media. The use of AI in mental health has been useful in every aspect and stage of mental health - from monitoring, assistance and evaluation to providing a cost-effective, scalable, and qualitative improvement of mental health therapeutic outcomes. However, there is a serious lack of research and assistive tools in providing real-time patient feedback to measure aspects and overall therapeutic outcomes of psychotherapy. To this end, we propose a novel metric of *trust* in mental health dialogue systems. Specifically, every patient's utterance in a counseling dialogue is scored on a scale that signals the degree of trust developed in the patient towards the therapist at any point in the therapy session. The contribution of this work is twofold (a) we provide a concretized definition of the novel metric of *trust* in mental health dialogue systems and a clear annotation framework that scores the strength of trust developed between a patient and therapist during counseling. (b) We discuss various strategies to model trust correctly and finally model it as a knowledge-guided time-series forecasting problem. We perform extensive experimentation and benchmark trust on various classical and modern methods of time-series forecasting, with our best model achieving an MSE loss of 0.0017.

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ABBREVIATIONS

iiitd	Indian Institute of Technology, Madras
RTFM	Read the Fine Manual

NOTATION

r	Radius, m
α	Angle of thesis in degrees
β	Flight path in degrees

CHAPTER 1

INTRODUCTION

Mental health has become a critical global healthcare concern, exacerbated by changing lifestyle conditions, growing individual aspirations, social media influence, and globalization. The World Health Organization reports a significant increase in mental health disorders worldwide, highlighting the urgent need for effective interventions (Organization, 2022; Organization *et al.*, 2022). The increasing prevalence of mental health issues demands innovative solutions to provide timely and effective care.

Digital and AI-assisted mental health interventions are increasingly recognized as necessary due to two primary reasons: (a) the exponential growth of mental health problems globally with the shortage, stigma and expensive nature of counseling and psychotherapy. (Moitra *et al.*, 2023) Also, (b) AI-assisted mental health solutions offer a promising alternative, providing cost-effective, scalable, and accessible care. Studies have demonstrated the effectiveness of AI-driven chatbots, which are particularly comforting and immediately available to users, meeting the need for asynchronous support. (Darcy *et al.*, 2021; Spadaro *et al.*, 2023; Baker, 2023; van der Schyff *et al.*, 2023) These digital tools leverage the familiarity and convenience of chat and social media apps, enhancing user engagement and adherence to mental health interventions.

Despite the growing acceptance of AI-powered chatbots and cognitive-behavioral therapy in general(CBT), there remains a significant gap in the availability of assistive tools to monitor, evaluate, and analyze patient responses comprehensively. Current solutions often lack the capacity to discern subtle aspects such as the accurate point of concern, the degree of vulnerable opening-up, and the patient's current feelings or emotions. These limitations hamper the ability to gauge the overall therapeutic outcome effectively. Recent studies highlight how clients react to counselors' strategies, how such reactions affect the final counseling outcomes, and how counselors can adjust their strategies in response to these reactions (Li *et al.*, 2023). The current research addresses this gap by introducing a novel approach to understanding a core contributor to therapy's success: the patient's trust in the therapist.

The therapeutic alliance is one of the most robust mechanisms of change in psychotherapy interventions and is defined as a collaboration between the patient and therapist on the tasks and goals of treatment, along with an emotional bond. This is important, as it allows for the *exploration of vulnerable issues by decreasing client's defensiveness and increasing their self-acceptance*. This therapeutic bond is fostered through *trust*, acceptance, empathy and genuineness. (Beatty *et al.*, 2022)

Herein, we discuss and define trust in mental health. Trust means one is willing to depend or intends to depend, on the other party with a feeling of relative security, in spite of lack of control over that party, even though negative consequences are possible. In other words, trust is the willingness to demonstrate vulnerability in the presence of others based on the belief that another party's behaviors are benevolent and will be responsive to the needs of others in a predictable and dependable manner. It is accompanied by a feeling of relative security. *Specifically, the trust of a patient towards their therapist is characterized by (a) Sharing personal or detailed, sensitive information and (b), Opening up on the relevant point of concern.*

We now proceed to formally define the problem statement addressed in this work: **"Accessing increase in real-time trust of a patient towards their therapist during mental health counseling conversation."**

To this end, we first propose a comprehensive framework of annotation guidelines designed to assess the degree of trust a patient develops towards their therapist, using a scale from 0 to 5. Utilizing these guidelines, we have curated a novel dataset by tagging 214 dialogues from the HOPE Dataset (Malhotra *et al.*, 2022). In this dataset, a patient's final utterance just before the therapist's response is annotated according to this *trust scale*.

Finally, we model trust as a knowledge-guided time-series forecasting problem. We benchmark our results on three class of models - classical time-series models, like ARIMA; classical RNN-based seq-to-seq models, like LSTMs, etc.; and state-of-the-art time-series forecasting models like PatchTST, iTransformer, etc. Knowledge is infused in time-series forecasting via the utilisation of contextual semantics of counseling dialogue. We evaluate and compare our results on mean-squared-error (MSE) and mean-absolute-error (MAE), the standard metrics for time-series forecasting. The top-performing model, PatchTST, achieves an MSE of 0.0017.

Summarising, following are the contributions of this study:- (a) We define trust in the domain of mental health ; (b) We propose an annotation framework for tagging every response of a patient along a trust scale of 0 - 5 in a counseling conversation; (c) We present MENTALTRUST, a novel dataset of 214 dialogues, with every patient-response is rated on a degree of trust; (d) We model trust on a variety of methods, and provide our analysis on their correctness and viability. (e) We finally model Trust as a Time-series forecasting problem, guided by utterences' contextual knowledge, and perform extensive experimentation with various modelling approaches. The best model achieves an MSE of 0.0017.

Our MENTALTRUST dataset and the code for statistics analysis and experiments in this paper are available in our GitHub repository:

CHAPTER 2

BACKGROUND

2.1 AI in Mental Health

Mental health has emerged as a profound global concern, necessitating innovative solutions beyond traditional approaches. The rise of digital interventions, particularly AI-powered tools such as chatbots and diagnostic algorithms, has transformed the landscape of mental healthcare. Amidst growing demand and stretched resources, AI's ability to process vast datasets offers unprecedented efficiency and accuracy in diagnosis and treatment strategies.

Clinical trials and experimental research underscore the pivotal role of AI in mental health. For instance, AI has enhanced the diagnosis of mental disorders by analyzing patterns across diverse data sources, including medical records and social media activity. (Minerva and Giubilini, 2023; He *et al.*, 2023) Notably, AI applications like digital phenotyping, natural language processing, and interactive chatbots have shown significant promise. These tools not only facilitate early detection of mental health issues but also customize therapeutic interventions, making mental health support more accessible and cost-effective. Moreover, the integration of AI in psychiatric care challenges traditional models by potentially reducing the human labor needed, thereby addressing both the scarcity of mental health professionals and the rising incidence of mental disorders globally.

To summarise, AI's integration into mental health services is not merely a technological upgrade but a fundamental shift towards more dynamic, responsive, and patient-centered care, promising to reshape the future of psychiatric and psychological therapies. However, while AI holds the potential to revolutionize mental healthcare, responsible and ethical implementation is essential. (Olawade *et al.*, 2024)

2.2 Trust in Mental Health

The Plutchik wheel of emotions is one the early successful attempts to classify human emotions into 8 basic categories, (including trust), and provides a simply logical way to make sense of feelings (Plutchik, 1982). Here, trust is understood as the emotion which signals that *'something is safe'*. Trusting can help someone to be open, connect and build alliance. Figure 2.1 depicts the Plutchik's wheel.

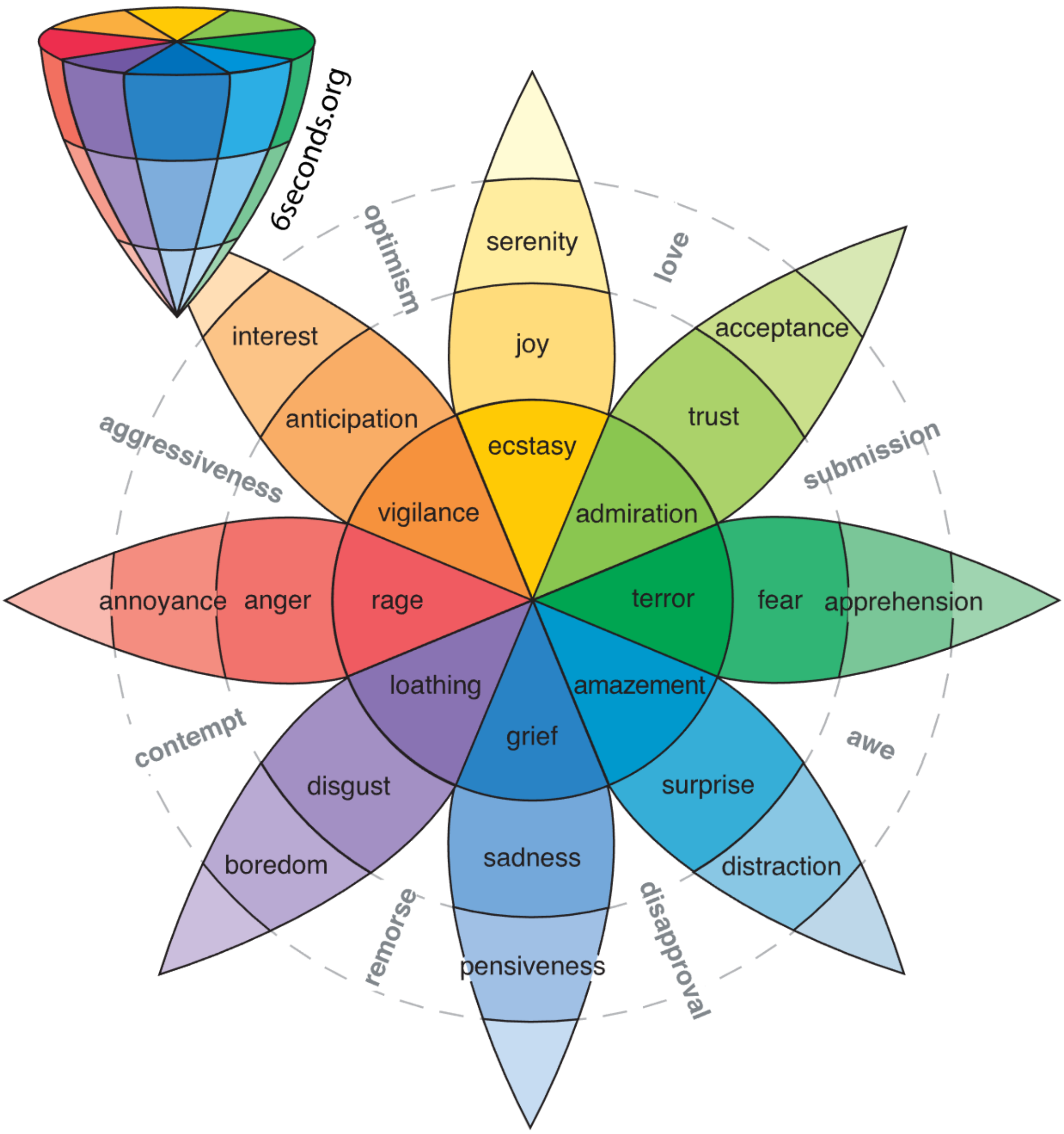

Figure 2.1: The Plutchik wheel of emotions.

Major theories in human psychosocial development emphasize the great importance of trust in building well-functioning relationships and holistic development of individuals (Bowlby, 1969; Erikson, 1963). Therapists' actions that are perceived by the patient as pro-relationship such as self-disclosure, fee reductions, and referrals for additional services, might be particularly useful for building trust in psychotherapy (Wieselquist *et al.*, 1999).

Currently, all therapeutic alliance scales contain at least one item referring to mutual trust. Although, there has been little research specifically on the patient's level of trust toward psychotherapists (Birkhäuer *et al.*, 2017). (Carter, 2024) attempts to define *therapeutic trust*, and differentiate it from ordinary trust. Carter argues that there are two kinds of trust - *default* therapeutic trust and *overriding* therapeutic trust, both of which relate to ordinary non-therapeutic trust differently. Default therapeutic trust refers to the basic level of trust that is implicitly present in most therapeutic relationships. It is an inherent part of any trust relationship here where the primary goal is for the trustee to take care of things as entrusted. However, overriding therapeutic trust is a more deliberate and intentional form of trust, aimed specifically at building or strengthening the trust relationship through the act of trusting. For example, imagine you have a teenage neighbor with a patchy record of responsibility. You decide to trust them to look after your house for the weekend, not just to get the task done, but with the hope that successfully completing this responsibility will help build their sense of reliability and strengthen your trust in them. This intentional effort to build trust through the act of trusting is an example of overriding therapeutic trust.

(Crits-Christoph *et al.*, 2019) aimed to develop and report preliminary psychometric analyses of a new brief measure to evaluate a patient's level of trust and respect for their clinician. Figure 2.2. However, none of these model the trust dynamics of the patient during the progress of a dialogue.

2.3 Time Series Forecasting

2.3.1 Definition

A time series is a sequence of data points collected or recorded at successive points in time, often at uniform intervals (Box *et al.*, 2015). It can also be thought of as a list of numbers, along with some information about what times those numbers were recorded (Beatty *et al.*, 2022).

Based on my last meeting with my doctor/therapist…

	Strongly Disagree	Disagree	Slightly Disagree	Neutral	Slightly Agree	Agree	Strongly Agree
1. I respect my doctor/therapist.	1	2	3	4	5	6	7
2. I am NOT sure my doctor/therapist is reliable.	1	2	3	4	5	6	7
3. I do NOT admire my doctor/therapist.	1	2	3	4	5	6	7
4. I have a high opinion of my doctor/therapist.	1	2	3	4	5	6	7
5. I do NOT have confidence in my doctor/therapist.	1	2	3	4	5	6	7
6. I do NOT hold my doctor/therapist in high esteem.	1	2	3	4	5	6	7
7. I trust my doctor/therapist.	1	2	3	4	5	6	7
8. I feel I can count on my doctor/therapist.	1	2	3	4	5	6	7

Figure 2.2: Preliminary development of trust-respect scale in counseling.

A time series can be mathematically represented as:

$$X_t = \{x_1, x_2, x_3, \ldots, x_n\}$$

where X_t denotes the value of the time series at time t.

2.3.2 Properties of Time Series data

The most important thing to note is that though the following factors are quite commonly found, a time series by definition may not have any or all of these factors collectively. Section 2.3 of (Hyndman and Athanasopoulos, 2018) discusses these properties and their optional nature along with examples.

A *trend* exists when there is a long-term increase or decrease in the data. It does not have to be linear. Sometimes we will refer to a trend as "changing direction", when it might go from an increasing trend to a decreasing trend.

A *seasonal* pattern occurs when a time series is affected by seasonal factors such as the time of the year or the day of the week. Seasonality is always of a fixed and known frequency.

A *cycle* occurs when the data exhibit rises and falls that are not of a fixed frequency. These fluctuations are usually due to economic conditions and are often related to the “business cycle”. The duration of these fluctuations is usually at least 2 years.

2.3.3 Types of Time Series Problems

Forecasting is the prediction of future values of a time series based on past observations.

Time series *classification* involves assigning labels to time series data based on their features. Applications include activity recognition and fault diagnosis.

Anomaly detection identifies unusual patterns that do not conform to expected behavior in a time series. It is used in fraud detection and network security.

Clustering groups similar time series together, which helps in identifying common patterns and behaviors within the data.

2.3.4 Time Series Forecasting

Time series forecasting is the process of predicting future values of a time series based on historical data. It involves identifying patterns, trends, and seasonal variations to make accurate predictions (Chatfield, 2000).

Given a time series $\{x_1, x_2, \ldots, x_t\}$, the goal of forecasting is to predict future values $\{x_{t+1}, x_{t+2}, \ldots, x_{t+h}\}$, where h is the forecast horizon. This can be represented as:

$$\hat{x}_{t+h} = f(x_1, x_2, \ldots, x_t)$$

where $\hat{x}_{t+h}$ is the predicted value at time $t + h$(Hyndman and Khandakar, 2008).

2.3.5 Modelling techniques for time series forecasting

Statistical Methods

ARIMA (AutoRegressive Integrated Moving Average): ARIMA combines autoregressive, differencing, and moving average components to model time series data. It is effective for stationary time series data by removing trends and seasonality.

Exponential Smoothing (ETS): This technique models time series data by exponentially smoothing past observations, placing greater weight on more recent observations.

Machine Learning Methods

Support Vector Machines (SVM): SVMs can be adapted for time series forecasting by framing the problem as a regression task.

Random Forests: An ensemble learning method that builds multiple decision trees and aggregates their results for improved prediction accuracy.

Deep Learning Methods

Recurrent Neural Networks (RNN): Designed to handle sequential data, RNNs maintain hidden states that capture temporal dependencies.

Long Short-Term Memory (LSTM): An extension of RNNs that mitigates the vanishing gradient problem, making them suitable for long-term dependencies.

Convolutional Neural Networks (CNN): Although originally used for image data, CNNs (including 1D CNN) can capture local patterns in time series data.

Recent SOTA methods in Time Series Forecasting

iTransformer (Liu *et al.*, 2024) improves time series forecasting by utilizing attention and feed-forward networks on inverted dimensions, embedding time points into variate tokens to capture multivariate correlations. This approach enhances performance, generalization, and efficient use of lookback windows, making it a robust alternative in the Transformer family.

TimeMixer (Wang *et al.*, 2024) leverages a multiscale-mixing approach with Past-Decomposable-Mixing (PDM) and Future-Multipredictor-Mixing (FMM) blocks to effectively disentangle and forecast complex temporal variations. This fully MLP-based architecture excels in both long-term and short-term forecasting tasks with efficient runtime performance.

PatchTST (Nie *et al.*, 2023) segments time series into subseries-level patches for input tokens and employs channel-independence to reduce computational costs and improve forecasting accuracy. This design retains local semantic information, reduces memory usage, and supports long-term forecasting, excelling in both supervised and self-supervised learning tasks.

Recent advancements have highlighted the capabilities of LLMs in this field, showing that they perform exceptionally well when predicting time series with distinct patterns and trends. However, they face challenges with datasets that lack periodicity. Studies have demonstrated that LLMs can determine the periodic nature of datasets through specifically designed prompts, enhancing their predictive accuracy. Moreover, incorporating external knowledge and using natural language paraphrases as part of the input strategy significantly improves LLM performance in time series forecasting. (Jin *et al.*, 2024)

2.3.6 Comparison of time series forecasting with other methods

Time series forecasting: Focuses on predicting future values based on historical data, handling **continuous data points *recorded* at specific intervals**. Common models include ARIMA, ETS, and LSTM.

Auto regressive language models: They predict the next word or sequence in natural language processing tasks, handling **discrete data points** (words or tokens) in a text sequence. Popular models include GPT family.

Stationarity in time series:

"Stationarity" of time series is, in principle, when the time series does not vary with time. For a time series to be stationary, the following three conditions are satisfied in a time series:
(a) constant mean, or no trend ;
(b) constant variance, or no cyclicity ;
(c) no seasonality (aka periodicity / autocorrelation).

The need for stationarity:

Autoregressive models, which are usually used to model time series, are essentially linear regression models. Assume Y_t is the value of time-series at t, then:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p} + \epsilon_t$$

Essentially, Y_t depends upon its own lags.

This works best when features ($Y_{t-1}, \ldots, Y_{t-p}$ etc.) are independent from each other or there is no correlation. This is important otherwise the model learns spurious correlations. Ex: If the season trend is hot and hotter, then next day might not be hot necessarily just due to trend. Model must learn from other intrinsic, independent variables determining the hotness of day. Put in other words, de-trending these components is like making time-series data into supervised learning data. So the method to solve time series problem classically is to convert it into normal, non-time series data and then solve.

2.3.7 Resources

Following are the github tool and libraries useful in the domain for time series modelling:

(a) statsmodels: A library in Python that provides classes and functions for the estimation of many different statistical models.

(b) sktime: A unified framework for machine learning with time series.

(c) pytorch forecasting: A PyTorch based package built on PyTorch Lightning framework for time-series-forecasting.

(d) Time Series Library (TSLib): An open-source library for deep learning researchers, especially for deep time series analysis. They provide a neat code base to evaluate advanced deep time series models or develop your model, which covers five mainstream tasks: long and short-term forecasting, imputation, anomaly detection, and classification.

(e) darts: A python library for user-friendly forecasting and anomaly detection on time series.

(f) prophet: A forecasting tool by facebook for producing high-quality forecasts.

2.4 Metric Assessment

Herein, we discuss some other metrics relevant to the understanding and measurement of trust: (Moyers *et al.*, 2016; Miller *et al.*, 2003)

1. Therapeutic Alliance: Therapeutic alliance, also known as the working alliance, refers to the collaborative relationship between a therapist and a patient. It is characterized by mutual trust, respect, and agreement on therapy goals and tasks. Research indicates that a positive therapeutic alliance is a significant predictor of treatment outcomes across various therapeutic modalities (Horvath and Luborsky, 1993).A robust alliance facilitates an environment conducive to trust, as patients feel understood, supported, and confident in their therapist's competence and intentions.(Bordin, 1979).

2. Therapeutic Outcome: Therapeutic outcome refers to the results of psychotherapy, including symptom reduction, improved functioning, and overall well-being. Positive outcomes are strongly correlated with the strength of the therapeutic alliance (Martin *et al.*, 2000). When patients experience improvements, their trust in the therapist's ability to provide effective treatment is reinforced. This is kind of an overriding therapeutic trust.

3. Respect: Respect in psychotherapy involves recognizing and valuing the dignity of the patient. It includes behaviors and attitudes that demonstrate this recognition, such as active listening, validating patient experiences, and maintaining a non-judgmental stance. Respect is crucial for building trust, as it ensures patients feel acknowledged and valued.(Wampold, 2015).

Labels:
Despise: Demonstrating disrespect or aversion, such as using derogatory language or questioning the therapist's qualifications. This reflects a lack of trust and respect.
Neutral: Neither particularly respectful nor disrespectful. Neutral interactions might not significantly impact trust.
Revere: Showing politeness, gratitude, and respect for the therapist's abilities. This label indicates high levels of trust and respect.

4. Self-Exploration: Self-exploration involves the patient's engagement in reflecting on personal thoughts, feelings, values, and experiences during therapy. It is a measure of the depth of the patient's introspection and emotional involvement. The Motivational Interviewing Skill Code (MISC) provides a framework for assessing self-exploration (Miller *et al.*, 2003).Higher levels of self-exploration indicate greater trust in the therapist, as patients are willing to delve into personal issues and engage in meaningful reflection (Truax and Carkhuff, 2007).

Definition of the Labels:
One (1) NO SE, minimal talk. No personally relevant material is revealed or discussed by the client during the session. If the clinician brings up personally relevant material, the client dismisses it or responds only minimally.
Two (2) Respond but not elaborate. The client may respond to and elaborate on personally relevant material that is brought up by the counselor, but does not add significant material or volunteers information in a mechanical manner or without demonstration of emotional feeling.
Three (3) Elaborate, not explore. The client does volunteer or elaborate on some personally relevant material beyond that directly asked for by the counselor, but does not readily explore it further.
Four (4) Explore. The client readily volunteers or elaborates on personally relevant material beyond that directly asked for by the counselor, evidencing some active thinking, feeling, and/or problem solving. The client may disFive (5):cover some new feelings, perspectives, or personal meanings.
Five (5) Explore and change. The client engages in active intrapersonal exploration, openly exploring values, problems, feelings, relationships, fears, turmoil, life-choices, and perceptions. Clients may experience a shift in self-perception.

Trust and Self Exploration:

In the realm of psychotherapy, understanding and measuring patient dynamics is crucial for effective treatment. Two important metrics in this context are trust and self-exploration. While both are interrelated and may share overlapping aspects, each metric captures distinct facets of the therapeutic process. Trust, as a novel metric, emphasizes the relational and interpersonal aspects of the therapeutic alliance, reflecting the patient's confidence and comfort in engaging with their therapist. On the other hand, self-exploration focuses on the depth of the patient's introspective journey, highlighting their willingness to delve into personal thoughts, feelings, and experiences. By delineating these two metrics, we aim to provide a comprehensive understanding of their unique contributions to the therapeutic process.

Trust is the 'state' of a patient towards the therapist which causes him/her to "open up" to the therapist. SE is one of the effects of trust, which causes the patient to 'self-explore' their values/feelings/judgements/decisions using the guidance/help of the therapist. They might also experience a shift in their perspective due to this process.

Trust, measured by 'opening-up', starts from 'refusal' to discuss the topic, which is explicitly saying not to discuss about that topic, or keeping quiet. This eventually would become 'digression', which is to discuss some non-relevant aspect about the topic/person, or just answer what's being asked by prompting.

Example: A woman hates her mother-in-law due to some very personal comments she made about her years ago. She might first refuse to discuss her(reject/refuse to open up), and later say a little about how she doesn't like her due to bad hygiene habits and/or annoying nature(digression→still not opened up on the core issue). All this while, she may or may not explore her feelings.

SE moves from a level of no SE, which **results in** no self-disclosure, then gradually towards some self-disclosure as a result of little 'self-exploration', and then maybe self-discovery and change in perspective due to it.

In higher levels of trust, the patient is not necessarily thinking and judging him/herself. In higher levels of SE, patient is exploring and judging themselves in just the presence(also guidance sometimes) of the therapist and might change due to it. However, in lower levels of both trust and SE, their would be no or little self-disclosure/opening-up, but that is okay since the low self-disclosure is "causing" the outcome of the low 'self-exploration'.

Example with dialogue 139

Let's just consider binary classes for both trust and SE. We have low/high trust and we have low/high SE. We shall now show examples for all 4 possible cases.

This is a conversation between a 17-yr old middle school girl and a therapist. I would suggest going through the entire dialogue once.

Line 33 The therapist has given a variety of pointers and aspects of life to select what is most important to her value system. The girl after much thought selects a few.

Since there is thought given for self-evaluation, it would be scored High SE, but since the girl doesn't open-up on anything and just answered what's being asked, it's scored low trust.

Line 89 The conversation has now moved on to the girl taking alcohol occasionally at parties with friends etc., just to fit in ... On the question of the therapist that she knows its illegal and risky but she still chooses to do it, the girl answers back by acknowledging and saying that it's a norm and everybody does it.

This is said without much thinking about herself(self-analysis), its implications on her and shows no signs or intent to change, hence it would be scored low SE. However, the girl acknowledges doing an illegal activity only because of a good trust of confidentiality being maintained by the therapist, hence its scored high trust.

Line 141 The girl herself takes the initiative and asks about helping his friends to quit drinking.

Since she is opening up and discussing the issue, how to deal with it and not running away from the issue(digression), it would be high trust. Also, because it involves exploring what she could do as a friend, her proactiveness, it's high SE as well.

CHAPTER 3

DATASET

3.1 Package Options

Use this thesis as a basic template to format your thesis. The `iiitd` class can be used by simply using something like this:

```
\documentclass[PhD]{iiitd}
```

To change the title page for different degrees just change the option from `PhD` to one of `MS`, `MTech` or `BTech`. The dual degree pages are not supported yet but should be quite easy to add. The title page formatting really depends on how large or small your thesis title is. Consequently it might require some hand tuning. Edit your version of `iiitd.cls` suitably to do this. I recommend that this be done once your title is final.

To write a synopsis simply use the `synopsis.tex` file as a simple template. The synopsis option turns this on and can be used as shown below.

```
\documentclass[PhD,synopsis]{iiitd}
```

Once again the title page may require some small amount of fine tuning. This is again easily done by editing the class file.

This sample file uses the `hyperref` package that makes all labels and references clickable in both the generated DVI and PDF files. These are very useful when reading the document online and do not affect the output when the files are printed.

3.2 Example Figures and tables

Fig. 3.1 shows a simple figure for illustration along with a long caption. The formatting of the caption text is automatically single spaced and indented. Table 3.1 shows a sample table with the caption placed correctly. The caption for this should always be placed before the table as shown in the example.

Figure 3.1: Two iiitd logos in a row. This is also an illustration of a very long figure caption that wraps around two two lines. Notice that the caption is single-spaced.

Table 3.1: A sample table with a table caption placed appropriately. This caption is also very long and is single-spaced. Also notice how the text is aligned.

x	x^2
1	1
2	4
3	9
4	16
5	25
6	36
7	49
8	64

3.3 Bibliography with BIBTEX

I strongly recommend that you use BIBTEX to automatically generate your bibliography. It makes managing your references much easier. It is an excellent way to organize your references and reuse them. You can use one set of entries for your references and cite them in your thesis, papers and reports. If you haven't used it anytime before please invest some time learning how to use it.

I've included a simple example BIBTEX file along in this directory called `refs.bib`. The `iiitd.cls` class package which is used in this thesis and for the synopsis uses the `natbib` package to format the references along with a customized bibliography style provided as the `iiitd.bst` file in the directory containing `thesis.tex`. Documentation for the `natbib` package should be available in your distribution of LaTeX. Basically, to cite the author along with the author name and year use `\cite{key}` where `key` is the citation key for your bibliography entry. You can also use `\citet{key}` to get the same effect. To make the citation without the author name in the main text but inside the parenthesis use `\citep{key}`. The following paragraph shows how citations can be used in text effectively.

More information on BIBTEX is available in the book by **?**. There are many references (**??**) that explain how to use BIBTEX. Read the `natbib` package documentation for more details on how to cite things differently.

Here are other references for example. **?** presents a Python based visualization system called MayaVi in a conference paper. **?** illustrates a journal article with multiple authors. Python (van Rossum *et al.*, 1991–) is a programming language and is cited here to show how to cite something that is best identified with a URL.

3.4 Other useful LATEX packages

The following packages might be useful when writing your thesis.

- It is very useful to include line numbers in your document. That way, it is very easy for people to suggest corrections to your text. I recommend the use of the `lineno` package for this purpose. This is not a standard package but can be obtained on the internet. The directory containing this file should contain a lineno directory that includes the package along with documentation for it.
- The `listings` package should be available with your distribution of LATEX. This package is very useful when one needs to list source code or pseudo-code.
- For special figure captions the `ccaption` package may be useful. This is specially useful if one has a figure that spans more than two pages and you need to use the same figure number.
- The notation page can be entered manually or automatically generated using the `nomencl` package.

More details on how to use these specific packages are available along with the documentation of the respective packages.

APPENDIX A

A SAMPLE APPENDIX

Just put in text as you would into any chapter with sections and whatnot. Thats the end of it.

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