Language Use in Teenage Crisis Intervention And the Immediate Outcome: A Machine Automated Analysis of Large Scale Text Data*

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Abstract

Evaluating the quality of crisis intervention is difficult due to the limited understanding of the interaction between crisis counselors and their clients. Research often needs to rely on small scale case studies because data is hard to collect and human language used during an intervention session is not easily analyzable. This paper utilizes a unique large data set of crisis intervention conversations in text format. Within a theoretical framework that helps us better understand the process of crisis intervention, a psycholinguistics approach is adopted to convert unstructured language into psychologically meaningful quantitative dimensions. The results from Multivariate Analysis of Variance show that certain word patterns of the clients are not only related to the immediate outcome of an intervention, but also vary across client subgroups. The same method also reveals that counselors employ different intervention styles in different client cases. Finally, this paper validates that crisis intervention quality can be predicted with the language use patterns of counselors and clients.

1. Introduction

Suicide has always been a serious threat to young people. For adolescents[1] between the age of 15 and 24, suicide is the second leading cause of death[2], taking away more than 4,600 lives a year[3]. While suicidal thoughts can take various roots, the behavior is often triggered by a crisis (Brent et al., 1993). Loss of families, broken relationship, being bullied at school – the association between crisis and suicide promotes the emergence of crisis intervention services, especially telephone-based helplines, as one of the earliest suicide prevention efforts in the United States. Back in 1958, the Los Angeles Suicide Prevention Center (LASPC) was established "for the evaluation, referral, treatment, follow-up and overall prevention of suicidal behavior" (Suicide Prevention Center of Los Angeles, 1966). Initiated by a group of psychologists, psychiatrists, nurses, and social workers, it gradually developed into a volunteer paraprofessional organization. Due to its efficiency and scalability, this volunteer-professional blended staffing structure soon got adopted by various crisis services that were inspired by LASPC.

The rationale behind crisis intervention services had been articulated even before LASPC was founded. Besides the clear link between critical stress events and suicide, as revealed by psychological autopsy research, Shneidman and Farberow (1961) point out that suicide is usually contemplated with psychological ambivalence, meaning the wish to die coexist with wishes to be rescued and saved, as reported by surviving attempters; this ambivalence sometimes results in a "cry for help" that can be addressed by trained counselors. Furthermore, because volunteer

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[1] Adolescence is defined as a transitional developmental period between childhood and adulthood (Berman and Jobes, 1995). In this paper, teenager and adolescence will be used interchangeably, referring to young people between the age of 15 and 24.
[2] Based on analysis of epidemiologic data in the United States reported by National Center for Health Statistics, various years.
[3] Statistics reported by Center for Disease Control and Prevention.

paraprofessional crisis services are often available outside of usual office hours, they provide immediate support at the critical moment when an individual is in the "final common pathway to suicide" (Shaffer et al., 1988; Gould et al., 2007). Lastly, telephone-based crisis services also allow callers to maintain anonymity and control, making it a particularly favorable tool among adolescents (Berman and Jobes, 1995).

Although crisis intervention service possesses the aforementioned advantages, its effectiveness remains to be evaluated. And the evaluation involves a series of questions: how do the helpee and the helper interact during a crisis intervention? How to measure the outcome of a crisis intervention? What are some characteristics of the interaction that signal a successful crisis intervention? To answer these questions, two premises need to be met: first, a better understanding of the nature and process of crisis intervention; second, enough analyzable data to quantitatively monitor and assess a crisis intervention. Luckily, this research meets both premises. With a large scale crisis intervention conversation data set and building upon previous research, this paper is the first scholarly effort to conduct machine automated[4] evaluation of crisis conversations. It aims to answer three basic questions:

a. In the case of helpline intervention for teenagers, are certain language use patterns correlated with the immediate outcome of the treatment?
b. How do language use patterns vary across subgroups of the counselor and the teenager?
c. Can we predict intervention outcomes based on language use patterns?

This paper is divided into six sections. Section 1 is introduction. Section 2 reviews literature that is related to the process, characteristics and impact of crisis intervention. Section 3 describes

[4] The evaluation of crisis intervention usually relies on human judges, whereas this research analyzes crisis conversations with computer.

the unique data set utilized in this paper and important descriptive statistics. Section 4 lays out and discusses quantitative methods for feature extraction, subgroup analysis and prediction. Section 5, selected results are reported and explained. Finally, Section 6 concludes the paper.

2. Literature Review

There have been continuous scholarly efforts to better understand the nature, process and impact of a crisis intervention. These previous studies, however, often speak within different frameworks and do not always reinforce each other's findings. After close examination and comparison, this paper adopts the Hill Process Model as the over-arching framework guiding the helpee-helper interaction. Within this framework, characteristics of the interaction and their observed impact on intervention outcomes will be reviewed.

2.1 Framework for Interaction: The Hill Process Model

Research on crisis intervention grows out of the established field of psychotherapy. Over the course of his clinical experience, Hill developed a process model that "describes the interaction of both overt and covert behaviors of therapists and clients in therapy" (1992). According to the model, preexisting client and therapist characteristics, such as personality, demography and motivation, set the stage for the interaction. At any given moment during the intervention, the therapist would draw from both theory and clinical observations of the client to develop an intention for the impact he or she wants to make. The intention is then implemented through specific response modes. For example, to establish connection, the therapist may mimic the client's tone or echo his or her emotions. On the client's side, his or her mental status is affected by the therapist intervention, and the change (if any) will be transferred into specific response modes. For example, if the client feels supported, he or she may reveal more to the therapist. Finally, interactions between the client and the therapist will yield an immediate outcome that can be captured in different ways, such as the measure of change in anxiety level or suicidal ideation, and client self-reported feelings.

In summary, the Hill Process Model provides a comprehensive and flexible framework for observing and measuring behaviors of the two actors during an intervention[5]. Its flexibility and power also come from the 4 underlying assumptions: 1) the measures are pantheoretical, in other words, applicable to all forms of counseling and therapy; 2) the measures do not assume that certain therapist behaviors are the most appropriate, and always examine them under given intervention circumstances; 3) therapists, clients, and nonparticipant observers can adopt different perspectives of the same events, all of which are valid; 4) covert processes in an intervention should be given special attention, because they often cannot be captured by external observers. Based on the model and the assumptions, Hill and his colleagues developed two verbal response category systems that measure the therapist and the client behaviors.

Therapist Verbal Response Category System. According to Hill, “therapist response modes refer to the grammatical structure of the therapist’ verbal response, independent of the topic or content of the speech” (1992). The latest version of TVRCS includes nine pan-theoretical, nominal and mutually exclusive modes or five clusters: (a) supportive interventions (approval), (b) directive interventions (information, direct guidance), (c) questions (closed question, open question), (d) paraphrase (restatement, reflection, summary, and nonverbal referent), (e) interpretive interventions (interpretation, confrontation, and disclosure).

[5] A modified Hill Process Model will be presented in the Methodology Chapter.

Client Behavior System (CBS). "Client behaviors are overt actions that clients exhibit during therapy sessions" (Hill, 1992). CBS includes eight nominal, mutually exclusive categories for judging client verbal response modes: resistance, agreement, appropriate requests, recounting, cognitive exploration, affective exploration, insight, and therapeutic changes.

It is worth noting that both the therapist's and the client's verbal response modes put an emphasis on the grammatical structure instead of the content of the speech. Although previous studies unexceptionally rely on human judges to measure verbal response modes, this important feature opens the door to machine automated linguistic analysis if digital text data is available.

2.2 Counselor Behaviors in Crisis Intervention

The crisis intervention literature has seen much contribution towards measuring and evaluating counselor behaviors. And most of them adopt certain forms of check lists which are variations of the Therapist Verbal Response Category System. Bobevski and Holgate (1997) applied Hill's system in looking at characteristics of effective telephone counselling skills. They found that the more effective counselors made significantly less use of Minimal Encourager Responses, greater use of Information Provision and Direct Guidance Responses and greater use of Interpretations. Daigle and Mishara, in investigating intervention styles at telephone suicide prevention centers, adapted Hill's verbal response modes into a 20-category Helpers' Response List (1995,1997). Results suggest that the use of acceptance, approval, and incomplete thought is associated with immediate reduction of depressive mood and suicidal urgency, while too much use of the investigation/advice, reflection and rejection response modes tends to damp the immediate outcome. In their 2007 paper, Mishara and his colleagues took a further step to develop models that are exclusive for telephone crisis intervention based on literature review, surveys of crisis centers and professional judgments. Statistical analysis found that empathy and respect, as well as factor-analytically derived scales of what they call “supportive approach and good contact” and “collaborative problem solving” were significantly related to callers’ positive outcomes.

A natural extension of the counselor verbal response modes is the counselor intervention style, for which the directive vs. nondirective debate is the most heated. The existing literature has not yet agreed on a definition of counselor directivity. The concept is also operationalized in different ways. Beutler formally defined therapist directiveness as “the extent to which a therapist dictates the pace and direction of therapy and communicates a direction of needed change, as well as the overall predominance of control established by the therapist to elicit change” (2011). In terms of measurement, directivity is often approximated by theoretical orientations. For example, the cognitive and behavioral systems of psychotherapy are conventionally identified as more directive (McAleavey and Castonguay, 2014). This ongoing debate is driven by both academic and professional interests. In academic research, cluster analysis of counselor response modes reveals more general patterns. Back in their 1995 research, Mishara and Daigle grouped helpers’ behaviors into the “the Rogerian style” and “the directive style”. The Rogerian has a focus on empathy and genuineness, therefore incorporates more use of the acceptance, approval and incomplete thoughts techniques (Rogers, 1951); whereas for the directive, counselors usually put themselves in a more dominant position, utilizing more skills of orientation/investigation, information/suggestion/advice, reflection and rejection (Karno and Longbaugh, 2005). In the professional field, two informal protocols guiding how telephone helpers should interact with callers were inspired by the Samaritan Movement and practices at the Los Angeles Suicide Prevention Center. Practitioners of the former tend to engage in nonjudgmental active listening as a primary method, whereas centers learning from the LASPC focus more on defining problems, finding solutions, and making referrals as part of what is called the “collaborative problem-solving” approach (Mishara et al, 2007).

It is worth mentioning that the aforementioned terms of intervention styles have no clear definitions and are used inconsistently across different studies. For example, some researchers equal Rogerian with the non-directive, others combine terms into Rogerian active listening or directive problem solving. Besides the lack of consistency in naming, empirical analyses of the intervention styles sometimes yields results poles apart. Beutler’s meta-analysis of 12 psychotherapy studies reveals that therapist directivity often increases client reactance, thus having a negative impact on the treatment outcome. In evaluating different telephone intervention styles with suicidal callers at suicide prevention centers, Mishara and Daigle also found that reduction of depressive mood were linked with a nonjudgmental style that incorporates limited directive components (1997). In a more recent study on helper behaviors and short-term outcome in telephone crisis intervention, however, a more directive style is found to significantly benefit repeat callers in reducing suicide ideation (Mishara et al., 2007).

2.3 Client Behaviors in Crisis Intervention

In contrast, fewer crisis intervention studies are found that systematically measure client behaviors in crisis intervention. After developing the theory of client verbal response modes, Hill and his colleagues applied the measurement system in two case studies to categorize every client response unit and found *description* to be the most typical client response mode. In both sessions, clients decreased in description and increased in simple responses, insight, and silence. Also, the occurrences of client response modes follow certain patterns. For example, insight often occurred after silence, open questions, and confrontation (Hill, 1986). More recent crisis intervention studies tend to view client’s behaviors as part the intervention outcome. For example, in measuring crisis hotline outcomes, Kalafat and his colleagues employed human judges to rate and compare caller's crisis state at the beginning and at the end of their calls to 8 centers in the U.S (2007).

To summarize, the existing literature on verbal response modes in crisis intervention has the following limitations: 1) there is no unified framework guiding the systematic studies of counselor and client behaviors, making research findings incomparable; 2) all studies rely on human discretion for categorizing verbal behaviors, resulting in very limited sample size and the difficulty to scale. Given the two limitations, this paper will be the first scholarly effort to conduct a large scale machine automated linguistic analysis of both the counselor's and the client's behaviors during a crisis intervention. The analyses sit within a counselor-client interaction framework that is adapted from the Hill Process Model, and will be clearly targeted at achieving better intervention outcomes.

3. Data and Descriptive Statistics

The data set analyzed in this paper comes from an existing database of crisis intervention conversations owned and maintained by Crisis Text Line (CTL). CTL is a data-driven NGO start-up providing free crisis intervention to teens 24/7, covering the whole United States. Unlike any traditional mental counseling service, CTL reaches young people in crisis via a simple yet powerful media: text. A teen can text into the CTL platform anywhere, anytime and a trained specialist will respond quickly, helping the teen stay safe and healthy. Along with its revolutionary services, CTL has also accumulated a large volume of real-time crisis intervention data in text format. It’s a scarce resource for researchers and policy makers because, for the first time, we get the chance to see a relatively complete picture of the teenager mental problems in the U.S. and to draw critical insights from it.

To give more details, the data is at both the conversation level (conv_level) and the message level (ms_level). The conversation level database contains general information as when a teen (texter) texts in (enter the platform queue), when a counselor responses and start the conversation, when the counselor closes the conversation, what the texter’s main concern is, how the texter feels after the conversation, etc. While the message level database documents all the messages exchanged between the counselor and the texter, with personally identifiable information (PII) removed.

3.1 Filtering of Data

The original dataset contains 84,311 conversations and 3,894,776 messages gathered between 09/26/2013 and 12/01/2014. These conversations were handled by counselors at 12 crisis centers across the U.S. And Figure 3.1 summarizes this entire intervention process in a diagram. After a texter texts into the system, he or she automatically enters a queue, where he or she will be asked general questions with regard to his or her crisis status while waiting to be connected with a counselor. During the conversation, the counselor can choose to conduct risk assessment or perform active rescue depending on the situation. The conversation can last for any long, until the texter drops out or the counselor closes it. Finally, after the conversation is closed, the texter will be asked to rate the conversation and the counselor will fill out post conversation surveys.

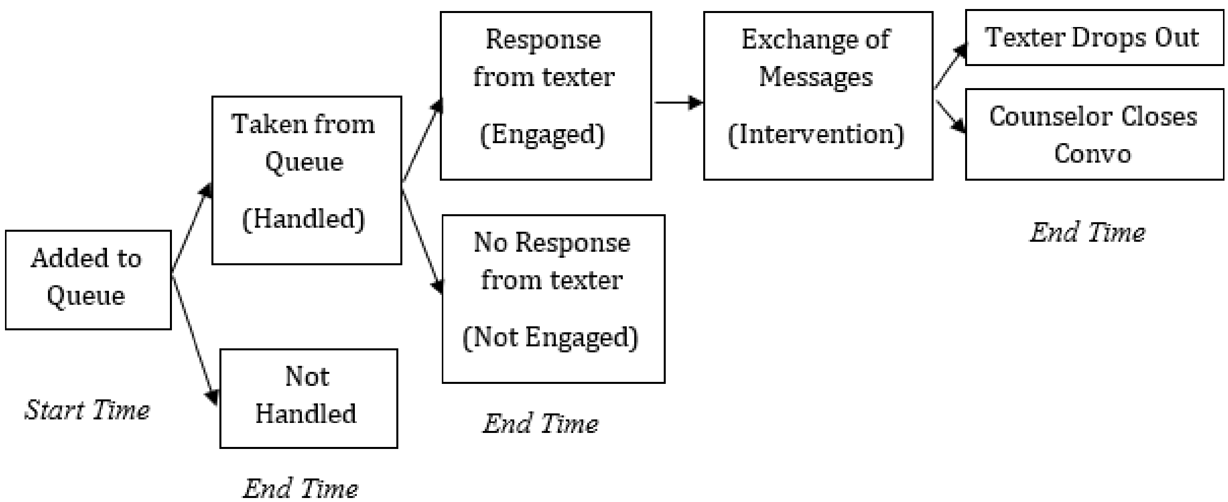


Figure 3.1: Intervention process at CTL. Engaged messages constitute 80% of all incoming messages.[6]

In order to obtain a valid data set for evaluating conversational characteristics against the outcome, proper data cleaning procedures need to be performed: 1) exclude system test messages; 2) exclude conversations that are for counselor training purposes and do not have a real texter; 3) exclude conversations marked as prank, business, and wrong number; 4) remove all non-engaged conversations with no back-and-forth of messages between the texter and the counselor; 5) retain only the conversations that are rated by the texter[7]. After filtering the data,

[6] The intervention process diagram is adapted from a work by Neolle Sio at Pivotal Lab.
[7] This may induce bias in the selected sample, but is unavoidable for the purpose of evaluation.

we are left with 15,187 rated conversations that have 27,970 unique texters, 509 unique specialists, and 3,665,063 messages that are roughly split half-and-half between texters and counselors.

3.2 Descriptive Statistics

The descriptive statistics presented in this section serve two purposes: first, provide better understanding of the sample through analysis of conversation meta-data; second, explore what factors may affect texter rating before modeling efforts. The original exploratory analysis investigates 23 variables in total, but only meaningful results are presented with visuals. And key take-ways of each analysis are highlighted in the caption of the graph. Please note that these variables are mainly constructed from conversation meta-data, for the extraction of language features requires more complex techniques that will be discussed in the Methodology part of this paper.

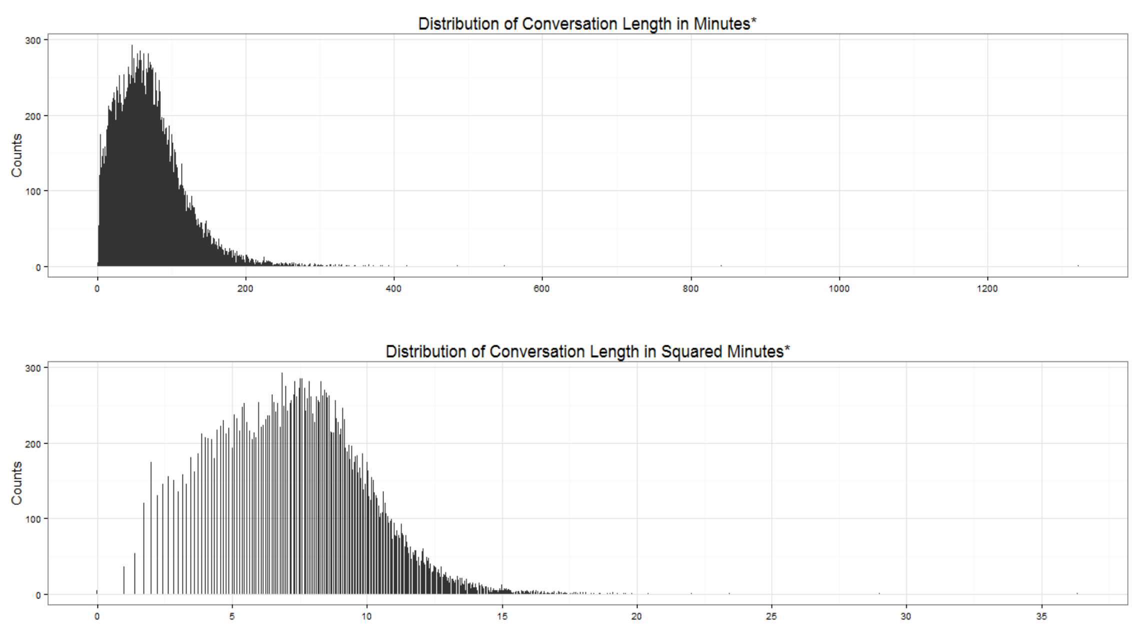


Figure 3.2: How long does a conversation last? A typical conversation lasts around 50 minutes (*mode* = 47). The distribution of conversation length has a long tail on the right (*sd* = 46), with more than 21% of the conversations longer than 2 hours, and the longest conversation taking almost 4 hours.

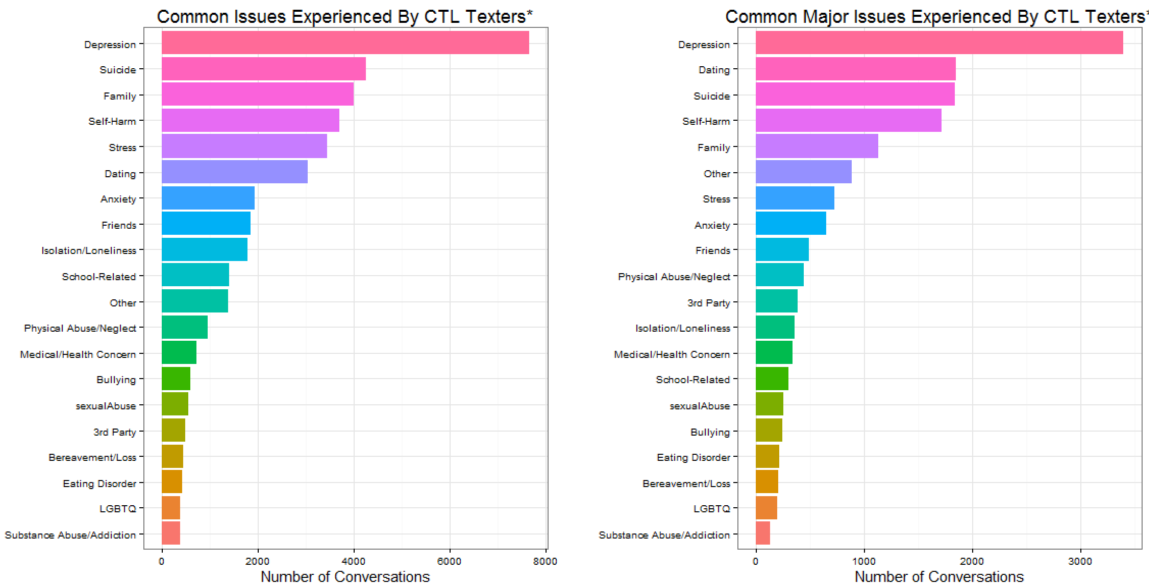
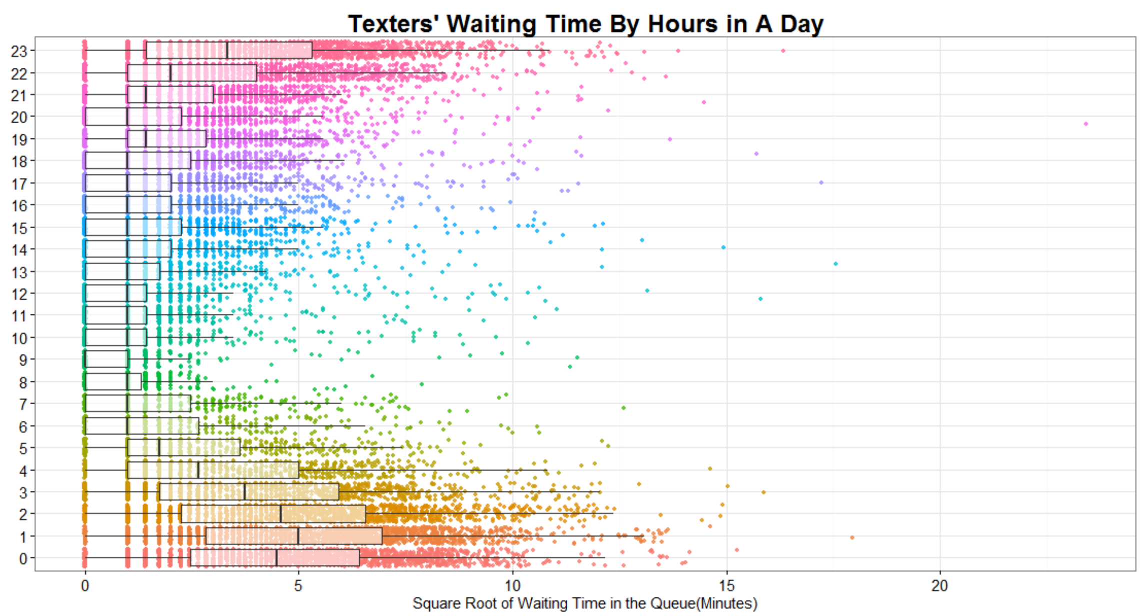


Figure 3.3: What crisis issues bring texters to CTL? Depression, Relationship and Suicide rank as the top 3 major issues that cause mental crisis of texters. Please note that crisis issues are often associated, meaning one major issue may trigger several side issues[8].



[8] The issue variables are extracted using keywords matching from the post conversation survey answers.

Figure 3.4: Limitation of Capacity at CTL. Due to limited counselor staffing capacity, texters sometimes have to wait for hours in the system queue. As evidenced by the density of dots in this plot, midnight usually sees the most texter volume but is also when the number of available counselors is most limited. It's been proved that longer waiting time will damp conversation engagement.

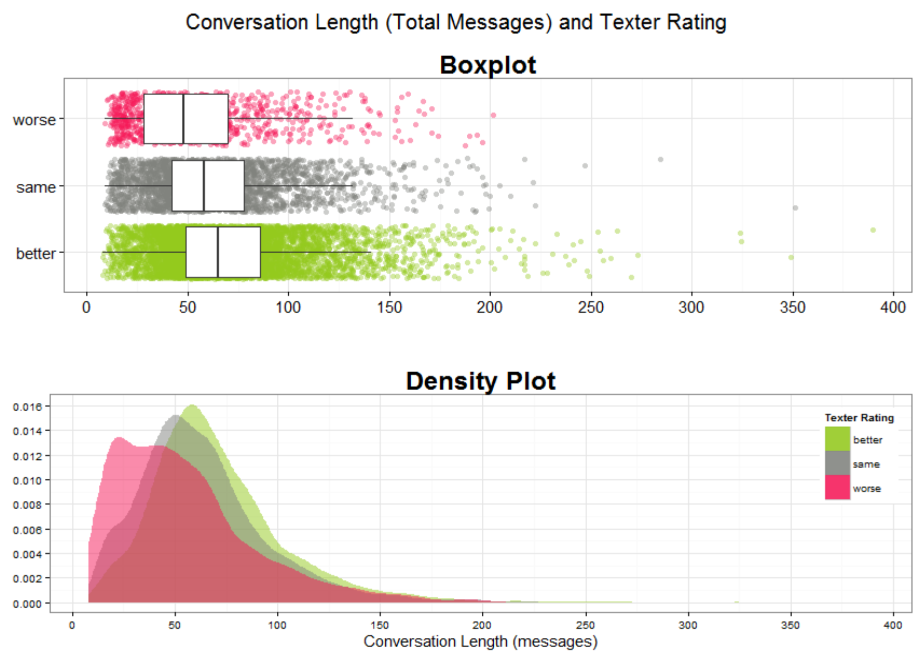


Figure 3.5: Longer conversation tends to have better outcome. Total number of messages is strongly and positively correlated with the rating given by texters at the end of a conversation. One possible explanation can be that more exchanged messages signal more active and in-depth communication between the texter and counselor, thus resulting in better intervention outcome.

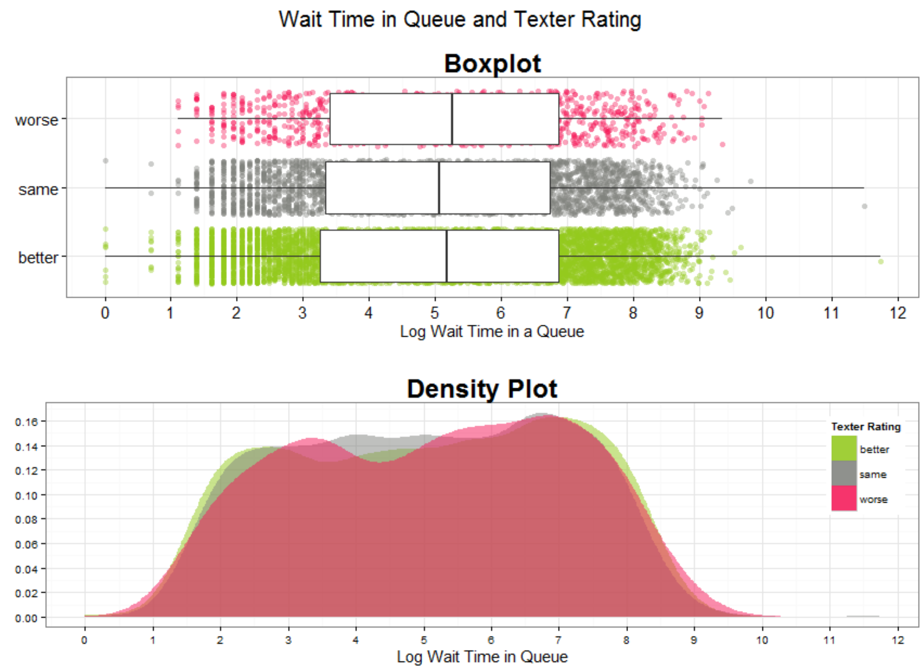


Figure 3.6: Once engaged, texter wait time does not affect intervention outcome. Surprisingly, it seems that texter wait time in the system queue only harms conversation engagement rate. As long as the texter is still willing to talk, intervention outcome is not affected by wait time.

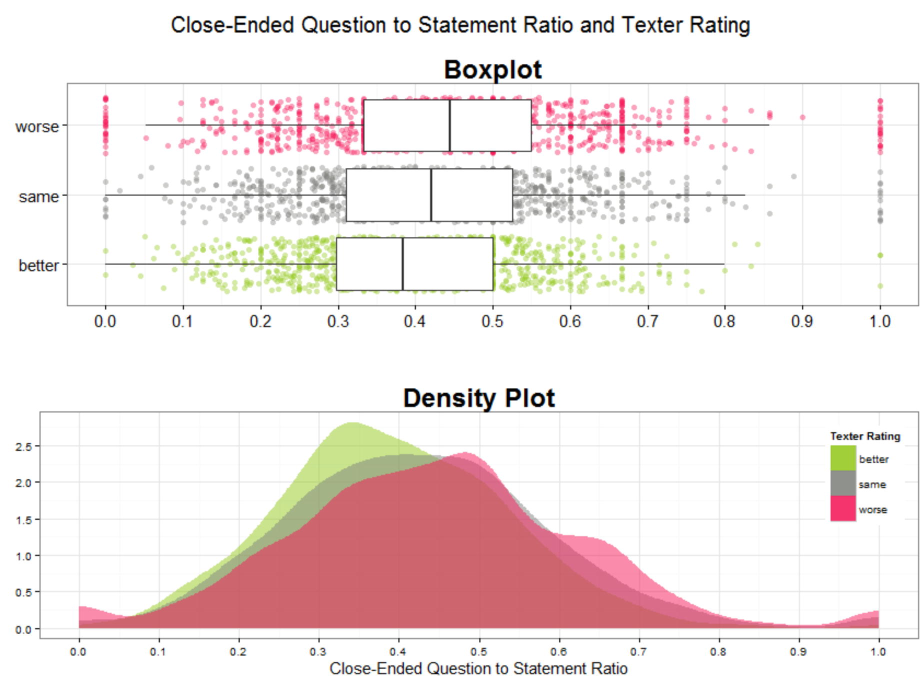


Figure 3.7: Counselor asking close ended questions will harm the intervention. Probing is an essential technique in crisis intervention to help counselor reveal texter's mental status. However, counselors need to ask the right question. As evidenced in the plot, asking close ended questions will only make texters feel worse. One possible explanation can be that when texters are in an unstable and agitated

state of mind, close ended questions force them to give an absolute answer that they themselves aren't even sure of, thus making them feel challenged, cornered, and want to hold back from sharing more with counselors[9].

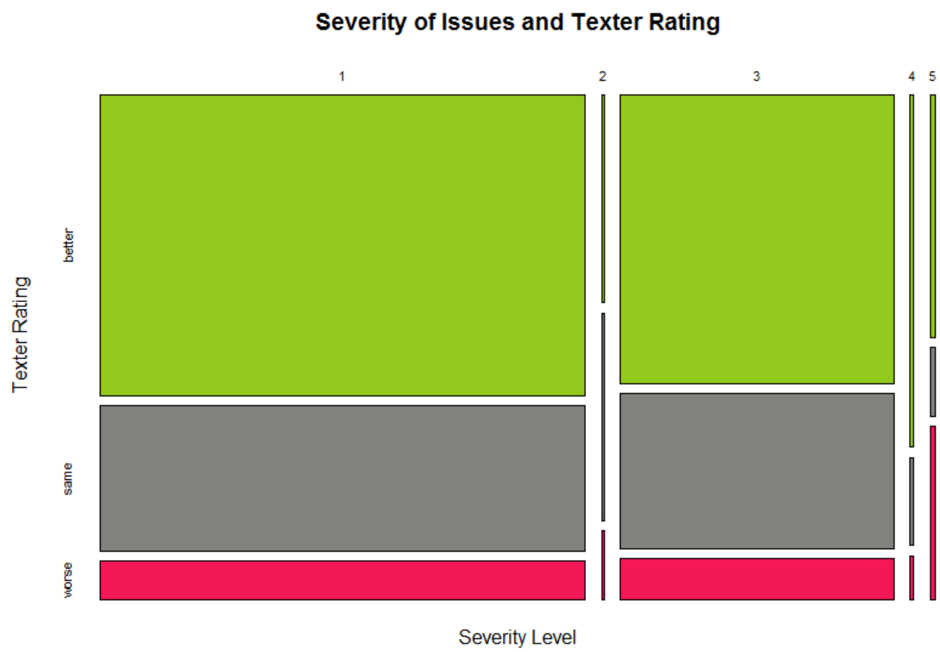


Figure 3.7: Conversations where active rescue is provided have worse intervention outcome as indicated by texter rating. Severity of issues is evaluated based on post conversation surveys and records for active rescue, and increases with levels. By comparing the proportion of conversations rated as better, same, worse in each level, we found that only level 5 has significantly more worse-rated cases. This finding encourages binning the variable to binary.

To summarize, exploratory analyses of the data find that the total number of messages exchanged is positively correlated with texter rating while asking too many close-ended questions tends to hurt intervention outcome. Besides, texters whose crisis situation requires active rescue are more likely to give worse ratings of the conversation. However, the information extracted from conversation meta-data is only the tip of the iceberg. The real treasure is still buried in the huge number of messages, waiting to be discovered.

[9] Closed-ended questions are spotted by matching messages that end with a question mark, and then exclude those that start with a list of words typical for open-ended questions, such as what, how, and why.

4. Methodology

Sitting on top of a hundred-megabyte level dataset composed of human generated text, this paper utilizes automated text mining techniques to convert unstructured data into psychologically meaningful features. Results of the dictionary-based feature extraction will then be fed into various statistical procedures as correlation test, MANOVA and predictive models to produce outcomes of interest. Within an adapted framework of the Hill Process Model, the analysis will focus on:

a. Extract language use features of the texter and the counselor from text messages and aggregate to conversation level;
b. Detect differences in language use patterns between 1) texters who rate the conversation as “worse”, those who give “same” rating, and those who give “better rating; 2) texters who are new, repeat and chronic[10] users of CTL’s services; 3) counselors whose conversations are rated as “worse”, “same” and “better”; 4) counselors who deal with new, repeat and chronic texters.
c. Predict conversation rating based on language use features and conversation meta-data.

Figure 4.1 demonstrates how the texter and the counselor interact during a crisis intervention, what pre-intervention factors influence the interaction, and the outcome of the intervention. In our case, pre-intervention variables are not available, the immediate outcome of the intervention is measured with texter self-reported rating, and actors’ response modes will be captured by linguistic features.

[10] New refers to first time user, repeat refers to texters that have the number of conversations between 2 and 20, chronic refers to texters that have more than 20 conversations with CTL. The distinction is made based on analysis of total service time consumed.

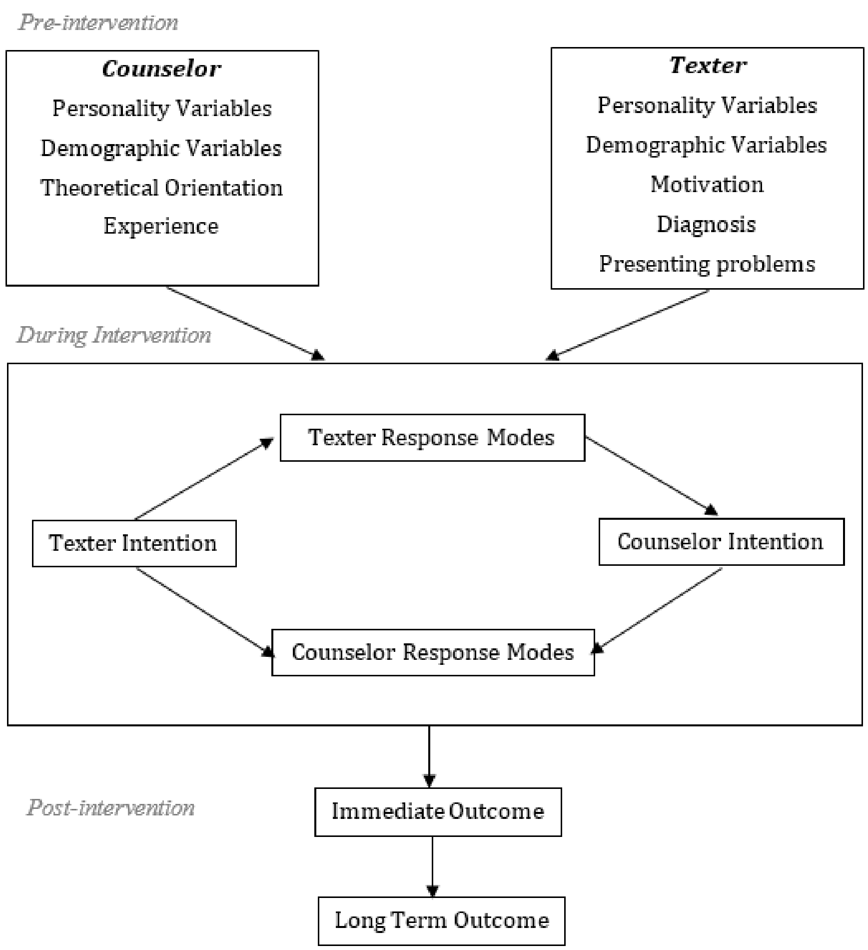


Figure 4.1: The Process Model of Crisis Intervention

To achieve the aforementioned goals, there are two quantitative stages in this research: feature generation and statistical analysis. Figure 4.2 summarizes methods utilized in two stages, each will be discussed in greater detail in the following paragraphs.

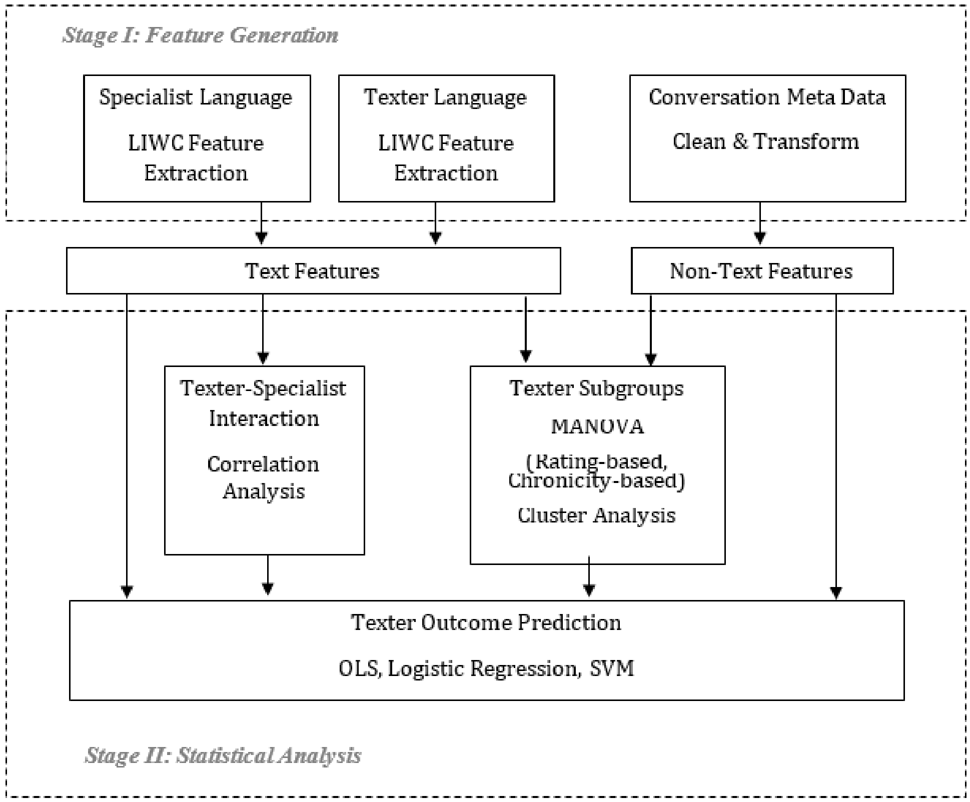


Figure 4.2: Quantitative Methods Diagram

4.1 Analyzing Texter Language: Dictionary-Based Feature Extraction with LIWC

The Linguistic Inquiry Word Count (LIWC) is the most popular dictionary-based text analysis program designed by James W. Pennebaker, Roger J. Booth, and Martha E. Francis[11]. With its 2007 version of dictionaries, LIWC evaluates any text along more than 70 linguistic dimensions, including positive or negative emotions, self-references, casual words, etc. These linguistic dimensions are hierarchical and are divided into 4 broad categories of linguistic processes, psychological processes, personal concerns and spoken categories (See Appendix 1). Because of its ability to catalog words into psychologically meaningful categories, LIWC has

[11] The latest version of LIWC software is available for purchase at liwc.net.

been extensively applied to various psychological domains. The outcome of the LIWC feature extraction will be numerical values of either total word count or percentage word count.

4.2 Analyzing Counselor Language: Measuring Directivity with LIWC

The same LIWC linguistic feature extraction is applied to counselor messages in each conversation. The selected raw linguistic features are then used to calculate leadership score (Pennebaker, 2011) and directivity score of the counselor following the formulas below.

$$Leadership_{simple} = (WordCount_z + we_z + you_z) - (ipron_z + i_z)$$

$$Leadership_{complex} = (WordCount_z + we_z + you_z + social_z)$$

$$-(ipron_z + i_z + negate_z + swear_z + excl_z)$$

$$CounselorDirectivity_z = \left(CounselorLeadership_{complex} - TexterLeadership_{complex}\right)_z$$

In formulas (1-3), all linguistic features are normalized because $WordCount$ is measured as absolute word count of messages sent by a texter or a counselor while other features are all in percentage word count. $CounselorDirectivity$ is measured as the difference between the two actors' leadership scores[12]. Positive $CounselorDirectivity$ implicates that the counselor is in a relatively dominant position during the intervention, while negative $CounselorDirectivity$ means the texter is taking the lead.

[12] The complex leadership score is used instead of the simple to calculate counselor directivity, because it is proved to possess better statistical properties.

4.3 Analyzing Subgroups: Pattern Detection with MANOVA

This paper also wants to zoom in on language use in texter subgroups and examine the potential cross-group pattern differences. To serve this purpose, analysis of variance (ANOVA) and the extended multivariate analysis of variance (MANOVA) come handy. ANOVA is a general procedure for partitioning the overall variability in a set of data into components due to specified causes and random variation (Krzanowski, 1988). It's an extension of $t - test$ when encountered with multi-level treatments. And MANOVA is used when more than one response variable needs to be evaluated. In this paper, one-way MANOVA will be applied to look at language use patterns in the rating and chronicity subgroups[13].

4.4 Predicting Texter Outcome

Texter rated conversations are only about 50% of all conversations at CTL, which means the quality of half of the conversations remain intractable. As the crisis intervention scales up, this would become a road blocker to more efficient services. Therefore, this paper will try to predict conversation outcome with both language use features and conversation meta-features. The conversation meta-features include total number of messages, total characters, texter-to-counselor message ratio, texter message frequency, texter chronicity, etc.

Multiple prediction algorithms will be tested and compared, including regular *OLS*, *logistic regression* and *support vector machine*. The dependent variable is texter rating in three forms.

$$TexterRating_{original}\ Levels = \ better, same, worse$$

$$TexterRating_{binary} Levels = better, not\ better$$

[13] Notice that our sample is imbalanced as conversations rated as worse constitute only 10% percent of the data. However, this should not be a particular concern because the partition between groups represents that in the population. We can therefore go with the normal weighted-mean approach.

$$TexterRating_{binary}Levels = worse, not\ worse$$

And independent variables will be language use features together with conversation meta-features.

$$TexterRating_{n \times 1} \sim TexterLanguage_{n \times m1} + CounselorLanguage_{n \times m2} + ConversationMetaFeature_{n \times k}$$

Here n equals the total number of conversations, $m1$ equals the total number of texter language features, $m2$ equals the total number of counselor language features, and k equals the total number of conversation meta-features. Dimension reduction methods may be applied to language features.

5. Results and Interpretations

This section presents results on language use feature extraction, subgroup MANOVA analysis and conversation outcome prediction. Section 5.1 discusses general performance of the LIWC. In Section 5.2, we check for differences in language use patterns across subgroups based on texter rating and texter chronicity. In section 5.3, we discuss counselor directivity together with texter chronicity and conversation outcome. Finally, section 5.4 compares performances of *generalized linear model (GLM)*, and *support vector machine (SVM)* with the dependent variable taking either three or two categories in predicting conversation outcome.

5.1 General Performance of LIWC

With the 2007 version of dictionaries, LIWC captured above 90% of all words appeared in the crisis intervention messages. Functional words, that is, pronouns and articles, constituted around 60% of all words. In text mining, functional words are often removed from corpus as they are considered to carry no real meanings. In psycholinguistics, however, the small and stealthy functional words can reveal people's personality, thinking style, emotional state, and connections with others. For example, the most commonly used word in spoken English, I, is used far more frequently by truth-tellers than liars (Pennebaker, 2011). Sometimes, functional words are even more honest than verbs and nouns. Appendix 1 provides a complete reference of 68 LIWC linguistic dimensions with variable names, definitions, example dictionary words, and their psychological implications that are pulled together from different sources.

5.2 Language Use Patterns in Texter Subgroups

Multivariate analysis of variance reveals significant differences in language use patterns of both texter subgroups. We can therefore dive into individual linguistic features to compare mean statistics across different levels of treatments.

Texter Rating Subgroup

Treatment Variable	Pillai's Trace	*F*	*df*	Residual *df*	Pr(>F)
Texter Rating	0.34	57.55	2	18280	$< 2.2e^{-16}$

Table 5.1: Significant Multivariate Effects for Texter Rating

As can be seen from Table 5.1, the multivariate effects of 68 linguistic features for texter rating are significant. Table 5.2[14] below selects 15 significant features to compare their mean statistics across three levels of texter rating.

Dependent Variables	Example Dictionary Words	Mean Statistics of Percentage Word Count		
		Better	Same	Worse
1st pers singular	I, me, mine	12.37	12.45	12.54
1st pers plural	we, us, our	0.35	0.34	0.26

[14] Variable names and example dictionary words in Table 5.2 can be found in LIWC Language Manual.

3rd pers singular	she , her, him	2.38	2.02	1.60
3rd pers plural	they, their, they'd	0.75	0.67	0.59
articles	a, an, the	3.29	3.26	3.05
future tense	will, gonna	1.08	1.00	0.86
prepositions	to, with, above	9.82	9.56	8.71
conjunctions	and, but, whereas	7.00	6.62	5.55
swear words	damn, piss, fuck	0.10	0.14	0.28
positive emotion	love, nice, sweet	5.27	4.49	4.04
negative emotion	hurt, ugly, nasty	3.51	3.84	5.71
cognitive processes	cause, know, out	19.26	19.85	17.55
space	down, in, thin	3.63	3.57	3.25
time	end, until, season	5.85	5.84	5.33
achieve	earn, hero, win	1.85	1.31	1.18

Table 5.2: Significant Univariate Effects for Texter Rating (at p<.001 level)[15]

Table 5.2 reveals some interesting results. In general, texters who gave a “better” rating to a conversation were more outward looking, using more *3rd person pronouns* (e.g. she, he, they); whereas texters who rated a conversation “worse” were more inward looking, using more *1st person pronouns* (e.g. I, me). Also, the “better” group demonstrated more positive experience in their language, using more *positive emotion words* (e.g. love, nice) and making more references to particular things (as evidence by higher rate of *articles*), *times* and *spaces*; whereas the “worse” group demonstrated more negative experience in their language, using more *negative emotion words* (e.g hurt, nasty). It’s worth noting that the *anxiety words* (e.g. worry, nervous) don’t seem to have a systematic difference across the groups, but the “worse” group

[15] A complete list of univariate effects for texter rating can be found in Appendix.

used *anger words* (e.g. hate, kill) and *sad words* (e.g. cry, grief) at a much higher frequency than the "better" group. Moreover, the "better" group revealed more recognition of group identity in their language, using *we words* at a higher rate; they were also more future oriented (as evidenced by more use of *future tense*) and mentioned more about achievements (more use of *achievement words*). The "worse" group, on the other hand, used astoundingly far more *swear words* than other groups.

Another interesting finding is that the "better" group demonstrated more complex thinking and cognitive processes in their language: they used more *prepositions*, more *conjunctions*, and more words representing *cognitive processes* (e.g. cause, know). After a traumatic experience, people usually relied on causal thinking to normalize the experience and relief their negative emotions. In this case, it looks like texters in the "worse" group were not able to employ causal thinking during the intervention process, and therefore receives worse treatment effects.

<u>Texter Chronicity Subgroup</u>

Treatment Variable	**Pillai's Trace**	***F***	***df***	**Residual *df***	**Pr(>F)**
Texter Chronicity	0.08	12.05	2	18280	$< 2.2e^{-16}$

Table 5.3: Significant Multivariate Effects for Texter Chronicity

As can be seen from Table 5.3, the multivariate effects of 68 linguistic features for texter chronicity are significant. Table 5.4[16] below selects 17 significant features to compare their mean statistics across three levels of texter chronicity.

[16] Variable names and example dictionary words in Table 5.4 can be found in LIWC Language Manual.

Dependent Variables	Example Dictionary Words	Mean Statistics of Percentage Word Count		
		Chronic	Repeat	New
words per sentence		34.99	62.80	60.26
1st pers singular	I, me, mine	12.82	12.56	12.28
1st pers plural	we, us, our	0.26	0.31	0.36
3rd pers singular	she , her, him	1.48	2.05	2.36
3rd pers plural	they, their, they'd	0.83	0.73	0.70
adverbs	very, really, quickly	5.91	6.46	6.34
prepositions	to, with, above	9.46	9.53	9.75
conjunctions	and, but, whereas	6.05	6.80	6.76
negations	no, not, never	4.22	3.97	3.72
number	second, thousand	1.28	1.57	1.67
family	daughter, husband, aunt	0.73	0.79	0.88
friends	buddy, friend, neighbor	0.36	0.53	0.59
positive emotion	love, nice, sweet	4.51	4.85	5.02
negative emotion	hurt, ugly, nasty	4.02	3.94	3.68
cognitive processes	cause, know, out	18.81	19.40	19.21
religion	altar, church, mosque	0.59	0.16	0.13

Table 5.4: Significant Univariate Effects for Texter Chronicity (at p<.001 level)[17]

According to statistics in Table 5.4, the "chronic" group, in other words, texters who had more than 20 conversations with Crisis Text Line, said significantly fewer *words per sentence*. It seems that more visiting times did not bring more depth to the conversation. Moreover, these group of people were generally in a worse mental state: they were more inward-looking (*1st*

[17] A complete list of univariate effects for texter rating can be found in Appendix.

person pronouns), expressed more *negative emotions*, and used more *negations* in their language. They also mentioned less about *family* and *friends*, demonstrated less positive experience (as evidenced by less *positive emotion words*, less specific reference of things using *number*). More importantly, they seemed not able to normalize their traumatic experience with proper *cognitive processes*. As revealed by their language, these texters communicate with counselors at a rather superficial level, using less *prepositions* and *conjunctions*. Interestingly, the "chronic" texters used significantly more words related with *religion*. One possible explanation is that some of them were already in the final pathway to suicide or were at least haunted by the thoughts to commit suicide, therefore would consider more spiritual things as compared to the other two groups.

5.3 Counselor Directivity

As reviewed in Section 2, two intervention styles emerged with the practices at crisis centers: directive and non-directive (Rogerian). Which intervention styles yield better texter outcomes? And do counselors adopt different intervention styles when faced with different types of texters? Using the *Counselor Directivity Score* calculated based on the LIWC dimensions, we have an answer.

Counselor Directivity and Texter Outcome

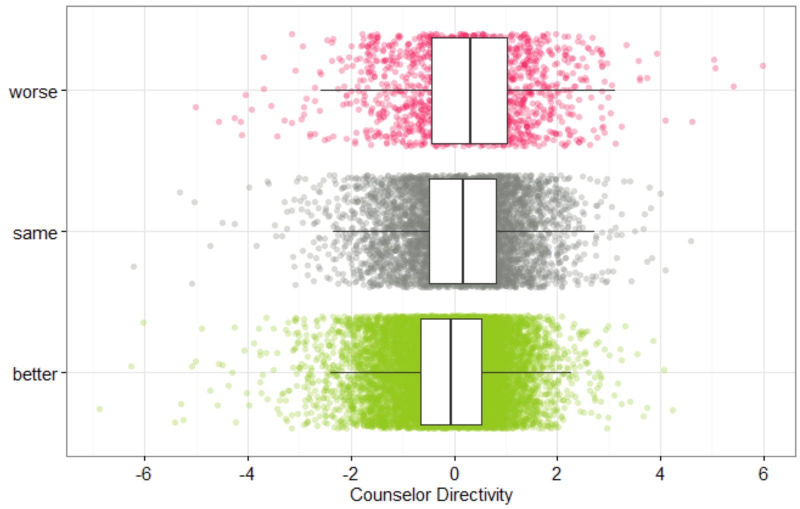


Figure 5.1: Counselors adopting a more directive intervention style get worse texter rating. As evidenced in this boxplot, non-directive styles seem to work better with texters at Crisis Text Line. Both the median and the mean for "better" conversations take negative value, meaning the texeter is in a leading position as compared to the counselor. The same statistics are positive for the "same" and the "worse" group, meaning the counselor is in a more dominant position.

Treatment Variable	***F***	***df***	**Residual *df***	**Pr(>F)**	**Mean Statistics**	
					Better	-0.10
Texter Rating	162.30	2	18280	$< 2.2e^{-16}$	Same	0.13
					Worse	0.26

Table 5.6: Significant Effects of Counselor Directivity for Texter Rating

Table 5.6 summarizes the ANOVA results for effects of counselor directivity on texter rating. It confirms the findings as we find in the boxplot.

Counselor Directivity and Texter Chronicity

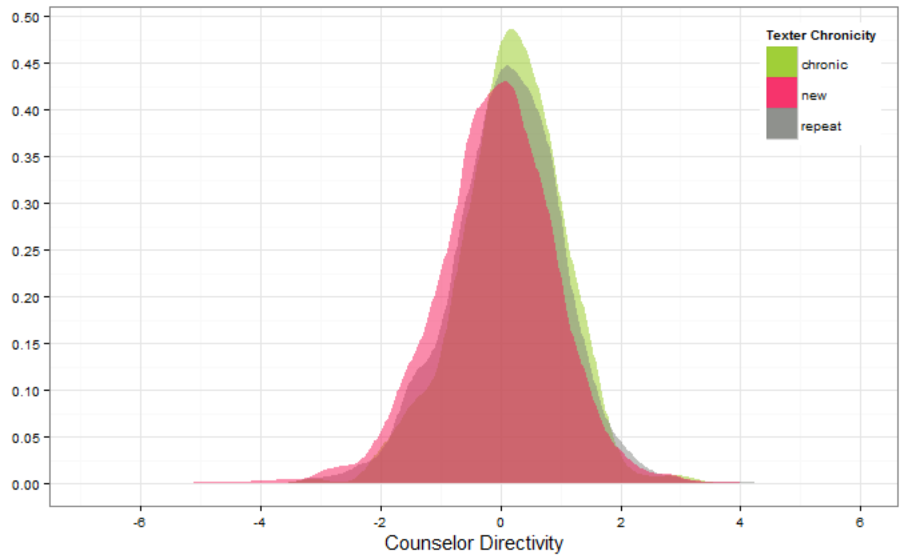


Figure 5.2: Counselors adopt a more directive intervention style with chronic texters. It's interesting that counselor do have different intervention strategies for different texters. As shown in the density plot, chronic texters are usually counseled in a more directive style. The intervention strategy with new texters varies more, but is in general less directive.

Treatment Variable	***F***	***df***	**Residual *df***	**Pr(>F)**	**Mean Statistics**	
Texter Chronicity	75.94	2	18280	$< 2.2e^{-16}$	Chronic	0.18
					Repeat	0.10
					New	-0.08

Table 5.7: Significant Effects of Counselor Directivity for Texter Chronicity

Table 5.7 summarizes the ANOVA results for the relationship between counselor directivity and texter chronicity. It confirms the findings as we find in the density plot. In addition to the interaction effect found between texter types and counselor intervention strategy, significant correlation of LIWC language features between the texter and the counselor is also found. The *distance correlation* reaches 0.65.

5.4 Prediction

Finally, we try to predict the texter rating with language features and conversation meta-features using different models. Each model was fitted to the training set of a random sample that is ¾ the size of the original. Then the fitted model is applied to the remaining test set for prediction and evaluation. *Accuracy*, *sensitivity* and *specificity* indicates the quality of prediction: *accuracy* measures the overall rate of correct classification, *sensitivity* is the proportion of true positive, and *specificity* is the proportion of true negative. Results are summarized in Table 5.8 below where D_{meta} stands for conversation meta-features, and D_{lan} stands for LIWC language features of both the texter and the counselor.

Model 1 is a baseline multinomial logistic regression with the 3-category (better, same, worse) texter rating as the dependent variable and the conversational meta-features as the independent variables. Judging from R_2 and *prediction accuracy*, conversational meta-features D_{meta} alone only explain a limited part of the variation in texter rating and also yields little predictive power. When language features are added as independent variables in Model 2, we see a jump in both the R^2 and the *accuracy*, meaning the use of language by texters and counselors is strongly correlated with texter rating. This confirms our assumption that language use influences and reflects how a texter feels for the intervention.

	Model	**Predictors**	**Dist. Correlation**	$\boldsymbol{R_2}$	**Accuracy**	**Sensitivity**	**Specificity**
1	GLM *(3 levels)*	D_{meta}	0.323	0.433	0. 501	---	---
2		D_{meta} & D_{lan}	0.601	0.513	0.700	---	---
3	GLM *(binary: better)*	D_{meta} & D_{lan}	0.654	0.547	0.751	0.473	0.915
4	GLM *(binary: worse)*		0.658	0.599	0.920	0.996	0.146
5	***SVM*** *(3 levels)*		0.611	0.543	0.706	---	---

6	SVM *(binary: better)*	0.649	0.565	0.750	0.460	0.922
7	SVM *(binary: worse)*	0.659	0.577	0.911	1.000	0.002

Table 5.8: Prediction Results for 4 Models

In Model 3, a binomial logistic regression is used to predict whether a texter will feel better after an intervention. With the independent variable binned into 2 categories, we are able to achieve better overall prediction *accuracy*. This may because that the difference of language use patterns between *better* and *not better* is more visible as compared to that across *same*, *better* and *worse*. Model 4 utilizes the same methods, but with the texter rating binned into *worse* and *not worse*. As can be seen, this yields the highest prediction accuracy of all models in Table 5.8, meaning the worse cases are easier to identify with language use. Comparing the *sensitivity* indicator and the *specificity* indicator, Model 3 is good at rejecting the *same and worse* conversations but mediocre at picking out the *better* conversations; while for Model 4, almost all the worse conversations get identified but a lot of the *same* and *better* conversations are mistakenly categorized as worse as well. This may due to the imbalance in our data that only around 10% of all conversations are worse.

Model 5-7 experiment another nonlinear machine learning technique *SVM* with the same independent and dependent variables utilized in the generalized linear model. This approach is as competitive as the linear approach in terms of prediction power. Also, within these three models, predicting the binary outcome of *worse* and *not worse* still yields the highest accuracy. The sensitivity and specificity indicators reveals a similar situation of the two binary outcomes as in the linear model.

Prediction results of the above models reveal important connection between language use and the crisis intervention outcome. Based on this baseline, dimension reduction methods can be applied to reduce noise in independent variables, and various other modeling techniques can be utilized to improve *accuracy*, *sensitivity* and *specificity*. More refined model selection can be achieved through cross validation. Also, the LIWC dictionary can be amended to better fit the crisis intervention context.

6. Conclusion

You are what you say. People's words reveal important information about their identity, emotions and relationships with others. In the context of teenage crisis intervention, language use during a counseling session has significant implications for the effectiveness of the treatment. On the one hand, certain word patterns, such as the use of *personal pronouns*, *emotion words*, and *cognitive words*, are not only closely related to the immediate outcome of an intervention, but also vary across texter subgroups. In particular, analysis of language use indicates that *chronic texters* do not benefit as much as *new texters* from crisis intervention services, but take up a large amount of counselor capacity. On the other hand, looking into counselors' language use, it is evident that the non-directive intervention style yields better texter outcome. Also, counselors are more likely to take the lead in conversations with chronic texters. Finally, combining language use features and conversation meta-data, we are able to predict conversation outcomes with confidence. By using this method, crisis intervention centers such as Crisis Text Line could achieve better services with close monitoring of conversational quality.

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APPENDIX

1. LIWC Feature Reference[18]

Dimension	Brief Definition	Example Dictionary Words	Psycho Implications
Linguistic Processes			
WC	word count		
WPS	words/sentence		deceptive/true
Sixltr	words > 6 letters		
Dic	dictionary words		
funct	total function words		engagement level of interatition
pronoun	total pronouns	I, them, itself	
ppron	personal pronoun	I, them, her	
i	1st pers singular	I, me, mine	inward looking, + sadness, + negmo, - power, - emotional distance
we	1st pers plural	we, us, our	group identity, + happiness, + posmo, + power
you	2nd person	you, your, thou	power +
shehe	3rd pers singular	she , her, him	outward looking, + anger
they	3rd pers plural	they, their, they'd	outward looking, + anger
ipron	impersonal pronouns	it, it's, those	
article	articles	a, an, the	thinking styles (categorical/dynamic)
verb	common verbs	walk, went, see	
auxverb	auxiliary verbs	am, will, have	
past	past tense	went, ran, had	past oriented, + sadness
present	present tense	is, does, hear	present oriented, + anger
future	future tense	will, gonna	future oriented, + sadness
adverb	adverbs	very, really, quickly	
preps	prepositions	to, with, above	thinking styles (complex/simple)
conj	conjunctions	and, but, whereas	thinking styles (complex/simple)
negate	negations	no, not, never	
quant	quantifiers	few, many, much	
number	numbers	second, thousand	
swear	swear words	damn, piss, fuck	
Psychological Processes			
social	social processes	mate, talk, they, child	
family	family	daughter, husband, aunt	
friend	friends	buddy, friend, neighbor	
humans	humans	adult, baby, boy	

[18] The dimension names, definition, examples dictionary words in this table can be found in LIWC Language Manual; the psychological implications are collected from the book *The secret life of pronouns* by James W. Pennebaker.

affect	affective processes	happy, cried, abandon	expressive writing (change over the course for repeat texter)
posemo	positive emotion	love, nice, sweet	
negemo	negative emotion	hurt, ugly, nasty	
anx	anxiety	worried, fearful, nervous	
anger	anger	hate, kill, annoyed	
sad	sadness	crying, grief, sad	
cogmech	cognitive processes	cause, know, out	
insight	insight	think, know, consider	
cause	causation	bacause, effect, hence	causal thinking/ non-causal
discrep	discrepancy	should, would, could	deceptive/ true
tentat	tentative	maybe, perhaps, guess	
certain	certainty	always, never	
inhib	inhibition	block, constrain, stop	
incl	inclusive	and, with, include	
excl	exclusive	but, without, exclude	thinking styles (complex/simple)
percept	perceptual processes	observing, heard, feeling	
see	see	view, saw, seen	
hear	hear	listen, hearing	
feel	feel	feels, touch	
bio	biological processes	eat, blood, pain	
body	body	cheek, hands, spit	
health	health	clinic, flu, pill	
sexual	sexual	horny, love, incest	
ingest	ingestion	dish, eat, pizza	
relativ	relativity	area, blend, exit, stop	
motion	motion	arrive, car, go	
space	space	down, in, thin	
time	time	end, until, season	
Personal Concerns			
work	work	job, majors, xerox	
achieve	achievement	earn, hero, win	
leisure	leisure	cook, chat, movie	
home	home	apartment, kitchen, family	
money	money	audit, cash, owe	
relig	religion	altar, church, mosque	
death	death	bury, coffin, kill	
Spoken Categories			
assent	assent	agree, ok, yes	
nonfl	nonfluencies	er, hm, umm	
filler	filler	blah, imean, youknow	

2. Significant Univariate Effects for Texter Rating

Variables	better	same	worse	Signif.
WC	391.8184	313.0576	235.3694	***
WPS	63.57249	56.66442	54.9029	***
Sixltr	11.47662	11.47759	11.32698	
Dic	91.27864	90.81468	87.97399	***
funct	59.50786	59.30956	55.16451	***
pronoun	22.49203	21.67209	20.73428	***
ppron	16.92424	16.33458	15.89988	***
i	12.37475	12.44866	12.53822	
we	0.351789	0.338908	0.261619	***
you	1.063837	0.857115	0.910913	***
shehe	2.383325	2.01881	1.598825	***
they	0.750375	0.670823	0.589738	***
ipron	5.567777	5.33748	4.834388	***
article	3.298523	3.258981	3.053437	***
verb	19.55459	19.63495	19.28919	*
auxverb	11.43749	11.70002	11.44168	***
past	3.651629	3.449466	3.3521	***
present	13.6939	14.10833	14.11514	***
future	1.084541	1.004117	0.862631	***
adverb	6.484382	6.347226	5.748425	***
preps	9.819948	9.563841	8.71805	***
conj	7.001089	6.62533	5.546762	***
negate	3.543724	4.218276	4.619519	***
quant	2.338263	3.004192	2.053412	***
number	1.459985	1.762336	2.337369	***
swear	0.103555	0.138334	0.275488	***
social	11.03057	10.37426	10.45744	***
family	0.863036	0.80224	0.782169	***
friend	0.56864	0.552397	0.501319	**
humans	0.673119	0.684641	0.708113	***
affect	8.663687	8.220568	9.676488	***
posemo	5.271439	4.478094	4.039806	***
negemo	3.508049	3.843088	5.707612	***
anx	0.757778	0.75433	0.717075	
anger	0.887957	0.947557	1.254831	***
sad	0.934064	1.124148	1.331194	***
cogmech	19.26115	19.85255	17.54446	***
insight	3.139922	3.099488	2.859944	***
cause	1.533248	1.45934	1.371281	***
discrep	2.102715	2.154067	2.181481	*

tentat	2.950935	2.924175	2.439606	***
certain	1.3772	1.362873	1.301781	*
inhib	0.499807	0.499443	0.523219	***
incl	4.295205	4.083309	3.555344	***
excl	4.476312	4.649392	4.148162	***
percept	2.358988	2.301182	2.192131	***
see	0.357051	0.328476	0.288344	***
hear	0.843607	0.826063	0.789319	
feel	1.128004	1.117079	1.090775	
bio	1.737394	1.886998	2.055131	***
body	0.448976	0.470574	0.501938	**
health	0.882673	1.003509	1.109431	***
sexual	0.269017	0.273236	0.343556	***
ingest	0.222403	0.247785	0.225613	*
relativ	10.33224	10.31466	9.40975	***
motion	1.379846	1.394827	1.30055	**
space	3.627787	3.569559	3.250044	***
time	5.849656	5.849203	5.33405	***
work	1.179583	1.156785	1.027262	***
achieve	1.851745	1.31181	1.183456	***
leisure	0.673267	0.601227	0.502906	***
home	0.40372	0.418499	0.369394	**
money	0.199955	0.231735	0.211094	***
relig	0.165409	0.137079	0.0972	***

3. Significant Univariate Effects for Texter Chronicity

Variables	Chronic	Repeat	New	Signif.
WC	339.1765	358.4538	354.1852	
WPS	34.98782	62.7956	60.25942	***
Sixltr	11.49935	11.50632	11.43131	
Dic	90.20326	91.07035	90.72175	
funct	57.524	59.03853	59.14628	*
pronoun	21.62203	22.04567	22.1638	*
ppron	16.11282	16.58843	16.74234	**
i	12.82368	12.56425	12.28297	***
we	0.2592353	0.312612	0.363236	***
you	0.7158529	0.933784	1.043168	***
shehe	1.481706	2.045241	2.356746	***
they	0.8314706	0.732227	0.696084	**
ipron	5.509118	5.457255	5.421421	
article	3.247824	3.250074	3.277989	
verb	19.92674	19.46934	19.60457	*
auxverb	11.76394	11.48881	11.52197	
past	3.775794	3.540121	3.581358	.
present	13.76618	13.78523	13.89846	
future	1.181559	1.036125	1.042094	**
adverb	5.911735	6.457155	6.340151	***
preps	9.463	9.526308	9.748219	***
conj	6.047235	6.797787	6.767544	***
negate	4.215647	3.965655	3.717545	***
quant	2.371382	2.507002	2.504562	
number	1.280912	1.572605	1.67125	***
swear	0.1652059	0.134939	0.122571	*
social	9.314088	10.34907	11.16938	***
family	0.7354706	0.789212	0.878436	***
friend	0.3558529	0.528819	0.586361	***
humans	0.5498529	0.674341	0.687504	**
affect	8.437471	8.674069	8.596878	
posemo	4.505088	4.849683	5.016561	***
negemo	4.016235	3.938235	3.684	***
anx	0.9504706	0.805574	0.708187	***
anger	1.065	0.991271	0.892893	***
sad	0.8851765	1.050937	1.006929	**
cogmech	18.81356	19.39979	19.20613	**
insight	3.232441	3.125765	3.08356	.
cause	1.507912	1.501328	1.495244	
discrep	2.447235	2.112818	2.122028	***

tentat	3.3015	2.95129	2.84646	***
certain	1.257971	1.363842	1.372061	
inhib	0.5199412	0.501418	0.5014	
incl	3.390412	4.149107	4.211178	***
excl	4.200265	4.58871	4.439059	***
percept	2.345353	2.362152	2.302118	*
see	0.3344118	0.355819	0.333654	*
hear	0.9099118	0.811854	0.847562	*
feel	1.066706	1.16157	1.094021	***
bio	1.770882	1.864383	1.76739	***
body	0.5373529	0.479672	0.442548	***
health	0.8533235	0.958128	0.924104	*
sexual	0.1891765	0.265274	0.288072	***
ingest	0.2490882	0.252089	0.212953	***
relativ	9.865559	10.2896	10.22729	.
motion	1.309647	1.375972	1.380285	
space	3.484294	3.548242	3.603246	.
time	5.610676	5.900771	5.739792	***
work	1.295088	1.113312	1.189516	***
achieve	1.686059	1.616372	1.654826	
leisure	0.8162647	0.683114	0.598599	***
home	0.3437941	0.403798	0.407771	
money	0.263	0.192087	0.221427	***
relig	0.5852059	0.156056	0.133636	***