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Linguistic predictors from Facebook postings of substance use disorder treatment retention versus discontinuation

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ABSTRACT

Background: Early indicators of who will remain in – or leave – treatment for substance use disorder (SUD) can drive targeted interventions to support long-term recovery.
Objectives: To conduct a comprehensive study of linguistic markers of SUD treatment outcomes, the current study integrated features produced by machine learning models known to have social-psychology relevance.
Methods: We extracted and analyzed linguistic features from participants' Facebook posts ($N = 206$, 39.32% female; 55,415 postings) over the two years before they entered a SUD treatment program. Exploratory features produced by both Linguistic Inquiry and Word Count (LIWC) and Latent Dirichlet Allocation (LDA) topic modeling and the features from theoretical domains of religiosity, affect, and temporal orientation via established AI-based linguistic models were utilized.
Results: Patients who stayed in the SUD treatment for over 90 days used more words associated with religion, positive emotions, family, affiliations, and the present, and used more first-person singular pronouns (Cohen's d values: [−0.39, −0.57]). Patients who discontinued their treatment before 90 days discussed more diverse topics, focused on the past, and used more articles (Cohen's d values: [0.44, 0.57]). All $ps < .05$ with Benjamini-Hochberg False Discovery Rate correction.
Conclusions: We confirmed the literature on protective and risk social-psychological factors linking to SUD treatment in language analysis, showing that Facebook language before treatment entry could be used to identify the markers of SUD treatment outcomes. This reflects the importance of taking these linguistic features and markers into consideration when designing and recommending SUD treatment plans.

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Introduction

Though retention in substance use disorder (SUD) treatment is beneficial (e.g., reduces relapses (1,2)), retention *per se* is difficult (e.g., SUD treatment discontinuation rate around 17–57% (3)). To improve the retention rate, many studies addressed facilitators of SUD treatment retention and discontinuation (e.g., leave treatment prematurely) using either traditional methods (e.g., survey and clinical trials (4)) or big data (5). However, novel research using digital phenotyping and data-driven methods to monitor substance use-related behaviors has often lacked theoretical roots; many traditional studies emphasizing the self-report and demographic risk factors (e.g., age and gender, see the review from (2)) lack comprehensive analysis from large datasets. To bridge this gap, we both generated data-driven linguistic features and assessed theory-based sociopsychological risk factors via established machine learning language models, upon patients' two-year Facebook postings before entering treatment, to predict future SUD treatment outcomes.

By using social media language, such as Facebook postings, we can observe SUD patients' ecological attention, beliefs, motivations, and affects in an objective way that is still free and self-disclosed (5–8). Social media language can diagnose disorders with high accuracy, such as predicting depression diagnosis using pre-diagnosis Facebook language (9), identifying features that can be linked to personalities, tracking mental health changes, and evaluating individuals' risk for alcohol, tobacco, and substance use (9–17). Recently, a few studies have incorporated this novel method into the substance use disorder research (5). For example, using machine learning models, researchers extracted language from peer-to-peer discussion forums and

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successfully detected messages disclosing substance use recovery-related problems (e.g., discussion of substance use triggers), providing the possibility of prioritizing these concerns for subsequent interventions (18). These pioneering studies have demonstrated that social media language is capable of translating patients' online postings to SUD identification, intervention, and treatment outcome prediction (18–20).

Our goal is two-fold. We want to first explore and extract the linguistic markers that are associated with SUD treatment outcomes with closed-vocabulary (i.e., psychologically relevant categories of words) and open-vocabulary (i.e., automated generated clusters of words) approaches; we then want to confirm three widely addressed theoretical determinations affecting SUD treatment outcomes, including religiosity, emotions, and temporal orientation, via established language models.

Religiosity has been widely documented as a protective factor for SUD treatment retention (21–23). More generally, it has been demonstrated that religious beliefs and practices can reduce relapse, alcohol drinking, and substance use (24,25) and are preferred by many patients (26). For example, religion has been found to be protective against cigarette smoking and drinking, and relatively unaffected by marijuana use increases in society (27). Religious beliefs may fulfill this protective role by providing an intrinsic moral framework for individuals to recognize the purpose and meaning in life (28), and by enhancing self-efficacy and forgiveness (29–31).

Emotions also impact SUD treatment retention and discontinuation. Negative emotions have been associated with SUD treatment discontinuation, relapse, and more substance use (e.g., (32,33)). For example, using interviews, researchers (34) found that "negative emotions" are associated with younger adults' discontinuation from residential SUD treatment programs. This association has recently been evidenced in language analysis. For instance, more negative emotional words has been found in gambling disorder patients' narratives (35). Differently, positive emotions promote health, including broadening and building social, physical, and cognitive resources (36), increasing self-rated health and life satisfaction (37), facilitating flexibility in thinking (38), and reducing suicide risk (39). Difficulties in emotion regulation have also been associated with substance use and relapse (40,41), for example, greater non-alcohol substance use was related to difficulties in regulating positive emotions (42). Therefore, it is worth confirming if negative and positive emotions in language correlate with SUD treatment outcomes.

Temporal orientation (past, present, or future in language) is also a known marker of mental health and relapse (e.g., (43–45)). Focusing on the past has been linked to greater post-trauma distress (46) and more ruminative thoughts (47), and negative valenced past orientation language significantly predicts higher levels of online addiction (48). By contrast, the impact of present and future temporal orientation on mental health and substance use are not consistent. Some studies suggested that present-focused orientation is associated with higher life satisfaction (e.g., (49)), while some found that present temporal focus was correlated with worse mental health (e.g., greater depression and anxiety (50)), and more substance use (51). Similarly, although higher future-orientation has been linked to healthier lifestyles, such as drinking less, smoking fewer cigarettes (52), exercising more (53), and suffering from fewer substance-related problems (54); one (55) found baseline future temporal orientation was not associated with past 30-day alcohol use, and another found it was more beneficial for men than women in completing alcohol addiction therapy (56). To better understand the links between temporal orientations and SUD treatment outcomes, we, therefore, examined such links via word use frequencies and machine-learning calculated temporal orientation styles.

Besides these three, personal pronouns also need our attention when analyzing health-related language use. The usage of first-person singular pronouns, like "I", indicates greater self-focus, and can predict suicidality (57), social anxiety (58), and depression (44). Whereas, in SUD research, such associations are often overlooked and not consistent. For example, using the same language analysis method based on word count frequency, Linguistic Inquiry and Word Count (LIWC (59)), one (18) failed to predict future alcohol relapse with first-person singular pronouns extracted from online forums; another study (60) found that the use of first-person singular pronoun "I" was positively correlated with tobacco, alcohol, and other substance use via Facebook language analysis; while a different study (35) found gambling disorder patients use less first-person singular pronouns in narratives about the definition of addiction and relapse, compared with that in their narratives about the onset and maintenance of the addiction. It remains unclear how the use of personal pronouns could be associated with SUD treatment outcomes. The current study aims to explore this association using the same language analysis approach (LIWC).

Materials and methods

Participants

Participants were recruited from community-based intensive outpatient SUD treatment programs in the Philadelphia metropolitan area. See recruitment criteria and process in Figure 1. Upon study intake, participants completed a baseline demographic survey and consent to share Facebook language, followed by weekly assessments of relapsing for up to 26 weeks post-baseline. Participants who wrote at least 200 words across their Facebook status within 2 years before study intake were included in data analysis ($N = 206$, M $(SD)_{age} = 32.73$ (9.28) year-old, 39.32% females; 55,415 postings). Participants who responded to at least one weekly survey after 90 days post-baseline were categorized into "retention" group ($N = 79$, M $(SD)_{age} = 35.58$ (10.05) year-old, 46.84% females; 74.68% Black), while who responded their last survey before the 90 days post baselines were categorized into 'discontinuation' group ($N = 127$, M $(SD)_{age} = 30.95$ (8.33) year-old, 34.65% females; 54.33% Black). We defined the outcome as a binary variable because our goal is to identify specific linguistic features that are associated with treatment outcomes at 90-day, rather than when patients discontinue their treatment. We chose 90-day because the median length of completing the intensive outpatient SUD treatment program is around 90 days (61). Institutional review board (IRB) approval was obtained from University of Pennsylvania. See full sample characteristics in Table S1.

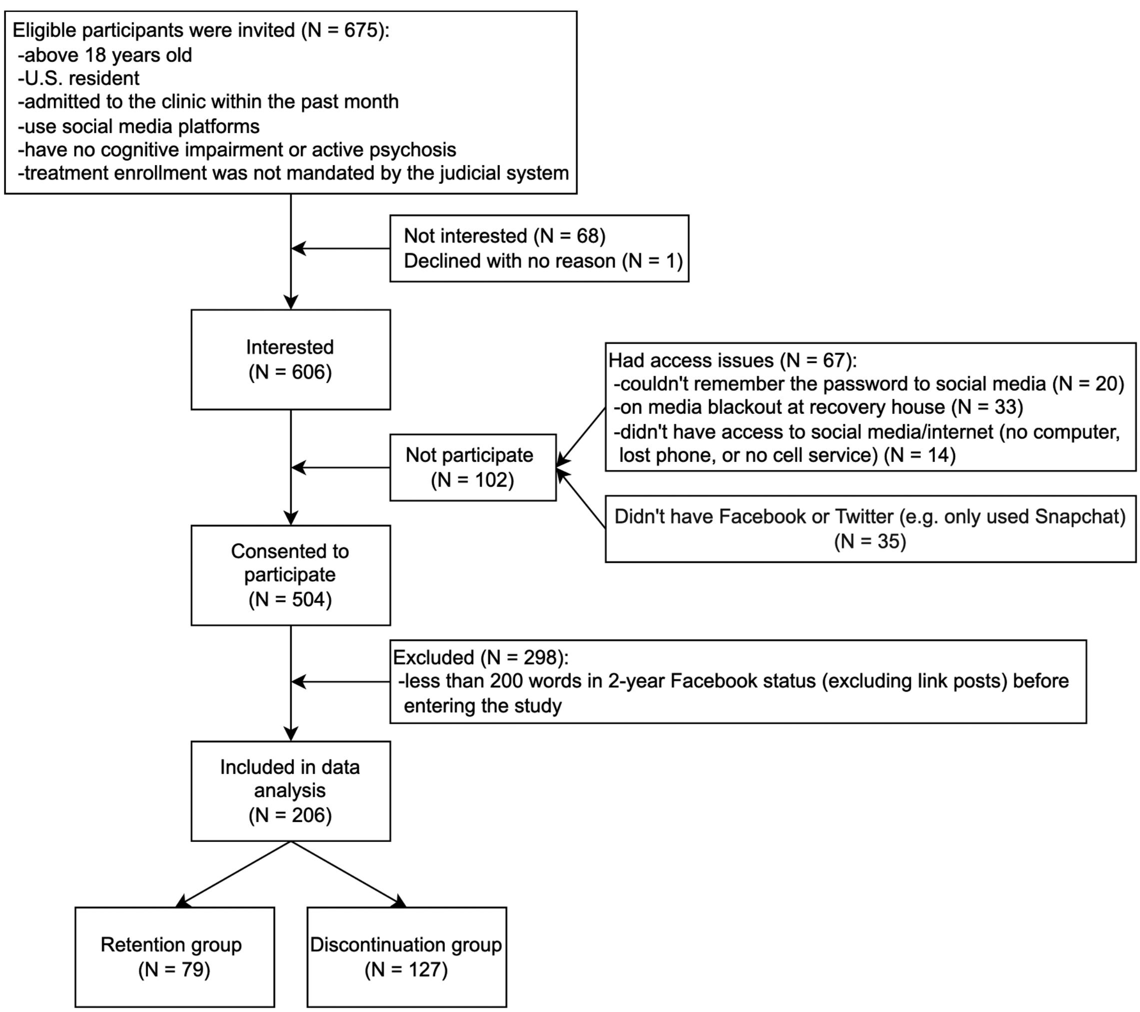

Figure 1. Participant recruitment process. Participants were recruited from community-based intensive substance use disorder outpatient treatment programs in the Philadelphia metropolitan area. Qualified participants should be over 18-year-old, have been admitted to the clinic within the past month since the day-1 of the current study (i.E., baseline), be active Facebook users, have no cognitive impairment or active psychosis, could provide competent consent, and their enrollment in the current treatment program is not mandated by the judicial system.

Predictive baseline

The data set used here is from the same data using in (13) but is slightly different. As opposed to improve prediction performance, our goal in the current study is to identify specific linguistic features to gain insights into individuals who successfully navigate treatment. We therefore first replicated Curtis' (13) main results (i.e., out-of-sample prediction of treatment outcomes from social media text) to establish a baseline for our subsample. Following the original methods (13), we replicated findings with an AUC of 0.73, though is smaller than the out-of-sample AUC of 0.79 in (13), is still within an acceptable range (62).

Linguistic analyses

Language preprocessing and feature extraction

We first converted the unstructured social media text into quantitative features for statistical analysis. Following standard preprocessing steps, we first removed non-English posts (7% in current data) using the "*langid*" Python package (63) via Differential Language Analysis Toolkit (DLATK (64)), which removed any posts that had a low estimated probability of English (less than 60%) or a high probability of Spanish (greater than 95%). Then, we concatenated all the posts from each participant into a single document and "tokenized" it (or split it up) into its constituent parts (e.g., words and punctuation) using DLATK's tokenizer built specifically for social media data, handling odd spellings and emoticons. Hereafter, all tokens are referred to as "words," with the understanding that single instances of non-traditional words, such as emoji, punctuation, and misspellings are also considered "words". Words were then numerically encoded with their relative frequency of occurrence within each participant: the number of times the word was written by the participant normalized by the total number of written words.

Closed-Vocabulary

We begin with a top-down (theory-driven) *word count approach* using a set of words and categories developed by psychologists, LIWC 2015 (59). LIWC is one of the most established dictionary methods for language analysis in psychological science (65). We first extracted the word frequencies for each participant, and then summed up all word frequencies within each of the 73 LIWC categories to calculate the relative frequency of each LIWC category for each participant. Cohen's d values (i.e., the difference in mean relative frequency of each LIWC category between outcome groups, normalized by the pooled standard deviation) were used to compute the effect size for each LIWC category. To calculate a significance level, we then ran a logistic regression with the relative frequency of each LIWC category as independent variables to predict the binary treatment outcomes (retention versus discontinuation) at 90 days. All p values associated with regression coefficients were corrected using the Benjamini-Hochberg False Discovery Rate correction across all p values (BH correction (66)), with a statistically significant level at $p < .05$.

Open-vocabulary

We complemented the above top-down approach with a bottom-up (data-driven) approach. For the entire collection of Facebook posts ("corpus"), we ran Latent Dirichlet Allocation topic modeling (LDA (67)) using DLATK along with the Mallet implementation of LDA (68) to create a set of automatically derived, semantically related groups of words ('topics'). We added additional preprocessing steps by limiting our corpus to only contain words that have been used by at least 2% of our participants and removing the 50 most frequent words, so that no single participant's language could drive the topic modeling process and that we removed words so common as to not provide any differentiation which might cause problems for LDA models (69). We created 200 topics, using all default settings except for alpha, a prior on the expected number of topics per Facebook post, which is set to 5. This value of alpha has previously been used to create LDA topics from Facebook data (70). For each topic, we estimated the relative topic usage for each participant and calculated the Cohen's d value between outcome groups. Again, all p values were calculated via the logistic regression, corrected with the BH correction, and significant at $p < .05$.

Theoretical factors and meta-linguistic features

Finally, we examined theoretical features but derived from published machine learning models: religiosity, affect, and temporal orientation. We also examine meta features that measure platform use: the total number of statuses posted, the total number of non-status update posts (i.e., shared links and images), and average word length. Using these features, we perform the same analysis as above (1): effect size is measured via Cohen's d values between the treatment outcome groups, and (2) a logistic regression is used to calculate significance levels of the theoretical factor's coefficient, where the theoretical factor is used as an independent variable to predict the binary treatment outcome, and (3) a BH correction is applied across the significance levels of all theoretical factors, with a corrected significance level of $p < .05$.

Religiosity. The religiosity scores estimating the probability of each participant being religious were generated from the model by Yaden et al (71). This model was built on a dataset of 10,595 Facebook users who posted at least 500 words across their statuses and have self-report religion status. This logistic regression model was trained to predict the binary indicator, set to 0 if the Facebook user self-reported agnostic or atheist and 1 otherwise, from a set of 2,000 LDA topics using a 10-fold cross-validation, producing an out-of-sample AUC of 0.84.

Affect. The affective ratings of each Facebook status consist of ratings on valence and arousal dimensions, following the circumplex model of affect (72,73), estimated by the model from Preotiuc-Pietro et al (74). This model was trained on 2,895 Facebook posts to predict the valence and arousal ratings annotated by two psychologists, and has achieved high predictive accuracy ($r = .65$ for valence and $r = .85$ for arousal annotations). For each participant in our sample, valence and arousal scores were averaged across all their status, respectively.

Temporal orientation. We use an existing AI-based classifier for estimating the temporal orientation of a message: whether it emphasizes the past, present, or future (75). This classifier was trained from an annotated dataset containing 4,302 Facebook posts and tested on 1.3 million messages with a classification accuracy of 0.72. This model was trained on a number of linguistic features: words and phrases, time expressions (e.g., "yesterday", "next week"), part of speech tags, LIWC categories, and overall post length (i.e., number of words within the post and the average word length). We applied this model to all posts in our data and as person-level features, stored the proportion of posts in each category: past, present, and future. Due to the sparsity of the results (i.e., many participants had proportions based only on a few posts), we smoothed the person-level estimates with a prior for the expected proportions based on Park et al (43).

Results

Closed-vocabulary

Correlation and comparison between LIWC categories and treatment outcomes (retention versus discontinuation) identified protective and risk LIWC categories (see Table 1). The more individuals talked about words relating to religion (e.g., "church"), positive emotion (e.g., 'love', 'nice', 'sweet'), family (e.g., 'daughter', 'dad', 'aunt'), affiliation (e.g., 'ally', 'friend'), and the more first person singular pronouns (e.g., 'I', 'me','mine') they used, the more likely they were to stay in the SUD treatment program. On the other hand, the more an individual used articles (e.g., 'a', 'an', 'the'), the more likely they would discontinue the SUD treatment.

Open-vocabulary

In general, words and phrases that were linked to SUD treatment retention focused on religion (e.g., "god", 'lord', 'pray') in a variety of contexts, including daily prayer (e.g., 'everyday', 'amen', 'mercy'), prayers for friends and family (e.g., 'family', 'friends', 'hospital', 'surgery', 'send', 'support'), greetings and positive feelings linked to religion (e.g., 'blessed', 'blessings', 'feeling', 'morning', 'amazing'). They also mentioned female family members positively and endearingly (e.g., 'loved', 'baby', 'miss', 'sister', 'mother', 'heart'), gave greetings (e.g., 'good', 'morning', 'hope'), and highlighted social events and celebrations (e.g., 'birthday', 'happy', 'big', 'wonderful', 'brother', 'shout'). See Figure 2.

Language extracted from individuals who discontinued SUD treatment revealed more diverse content. They discussed many aspects of daily life, including shopping (e.g., "find", 'store', 'shop', 'card'), pets (e.g., 'dog', 'cat', 'rat'), and dogs barking in the neighborhood (e.g., "walk", 'dog', 'door', 'house', 'neighbors'), (shooting) news (e.g., 'news', 'killed', "world", 'muslims', 'killed'), videos they watched (e.g., 'video', 'remember', 'challenge'), and miscellaneous topics related to backyard (e.g., 'back', 'fall', 'yard'). See Figure 2.

Theoretical factors and meta-linguistic features

Consistent with our findings in closed and open vocabulary, being estimated to be more religious in language, being more positive in sentiment valence, and being more temporally present focused in language, are positively correlated with remaining in SUD treatment; and more references to the past times is correlated with discontinuation (see in Figure 3). All results remained significant even after controlling for gender or race (if being black), *p*s < .05.

Table 1. LIWC categories predicting SUD treatment retention versus discontinuation at 90 days.

LIWC Super-category	LIWC Sub-category	Representative words	Cohen's *d*	*p*	95% CI L	95% CI U
Protective factors						
Personal concerns	Religion	God, pray, hell, soul	−0.56	.008	−0.65	−0.46
Affective processes	Positive emotion	love, good, LOL, happy	−0.53	.015	−0.62	−0.42
Social processes	Family	family, baby, mom, son	−0.49	.021	−0.59	−0.38
Total pronouns	1st person singular	I, my, me, I'm	−0.49	.024	−0.59	−0.38
	Personal pronouns	I, my, you, me	−0.44	.047	−0.55	−0.33
Drives	Affiliation	we, love, our, family, friends	−0.47	.021	−0.57	−0.36
Risk factors						
Total function words	Articles	the, a, an	0.44	.048	0.32	0.54

Protective factors refer to factors that predict treatment retention, risk factors refer to factors that predict discontinuation. SUD = Substance Use Disorder, LIWC = Linguistic Inquiry and Word Count, English 2015 category. 95% CI = 95% confidence interval, L= Lower, U = Upper. All correlations in the table were significant (*p* values were computed via logistic regression with a significance level at $p < .05$; BH *p*-corrected). Language source: Facebook language two years before participants entered a SUD treatment program.

Discussion

Integrating both social-psychological factors and natural language processing methods, the current study utilized pre-treatment Facebook language to identify the characteristics of individuals who stayed in SUD treatment as compared to those who discontinued SUD treatment at 90 days.

Religiosity is one of the major patterns observed in language use that are associated with treatment retention in the current study. Our findings replicated previous studies on religion benefiting health, well-being, and substance treatment retention (76–79). Religious beliefs could be protective because they can foster a positive self-focus, such as the development of self-regulatory strength, and help individuals to recognize the purpose and meaning in life (28). Talking about religious topics and mentioning religious words in the Facebook language (e.g., prayers) is communication about their religious beliefs and also an internal conversation to help people focus on themselves and develop their resistance and inner strength. This function could also help us to understand the unusual positive association between the use of first-person singular pronouns and SUD treatment retention in our findings. Previous findings have linked the high frequent use of first-person singular pronouns to negative mental health outcomes because most of these self-focused thoughts are usually negative, maladaptive, and ruminative (80). It is possible that the self-focused thoughts, reflected by the use of first-person singular pronouns in language, are impacted by religious beliefs (81), because religious beliefs are often linked to positive self-focus and self-enhancement, resulting in a greater emphasis on self-related responsibility and emotional states (82), which helps with SUD treatment retention. Future in-depth explorations of this association are needed.

We found that the language of people who stay in treatment reflected more social relationships, gratitude, and pleasant feelings in daily life and activities. Such feelings of amusement, love, and gratitude could be considered "low-approach" positive emotions (83,84), which could be experienced after a reward or goal is obtained, and further increases global attentional focus (83) as well as resilience (85). Such improvements could then become buffers when coping with challenges and conflicts from family and peers that could lead to substance use (85), remind people in recovery of their responsibilities, and nudge them to reach the life prior to or outside of substance use (86,87). Therefore, people who talked more about these positive feelings and social connections were more likely to stay in SUD treatment. On the other hand, as substance use has been considered a coping strategy with the dysregulation of positive emotions (e.g., avoidance of positive emotions (42,88,89)), expressing positive emotions on social media reflects these stay-in-treatment patients' ability to adaptively regulate their positive emotions to some extent, which might be beneficial to treatment completion and recovery.

We also found that treatment retention was linked to a more present temporal focus, while the treatment discontinuation was linked to a more past temporal focus. Our findings have supported the viewpoint that a present temporal focus has positive impacts on life (90,91), and the past temporal focus can lead to negative consequences (e.g., greater internet addiction and higher levels of emotional distress) (45). We did not replicate the positive links between present temporal focus and substance use shown in previous research (51), which often used self-report surveys to capture the emotional and attitudinal perspective of past, present, or future ("Taking risks keeps my life from becoming boring", "I often follow my heart more than my head" from Zimbardo Time Perspective Inventory; 52). Differently, we captured the linguistic

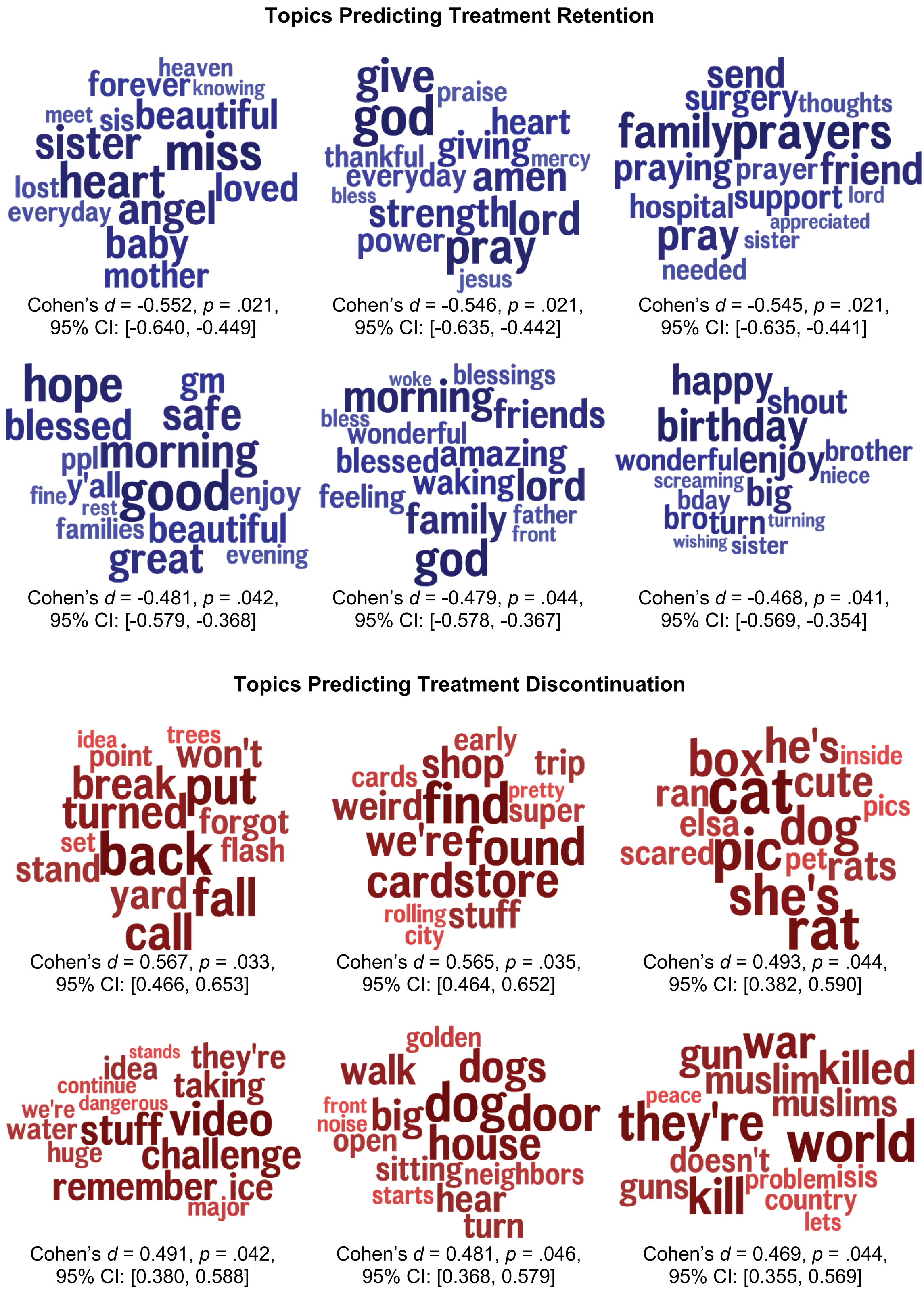

Figure 2. Topics predicting SUD treatment retention versus discontinuation at 90 days. Using latent Dirichlet allocation topic modeling, we created a set of semantically related groups of words ('topics') and estimated the relative usage for each participant. The Cohen's *d* value between the treatment outcome groups. All *p* values were computed via *t*-test of logistic regression coefficients; $p < .05$; BH p-corrected. SUD = Substance use disorder. 95% CI = 95% confidence interval. Language source: Facebook language.

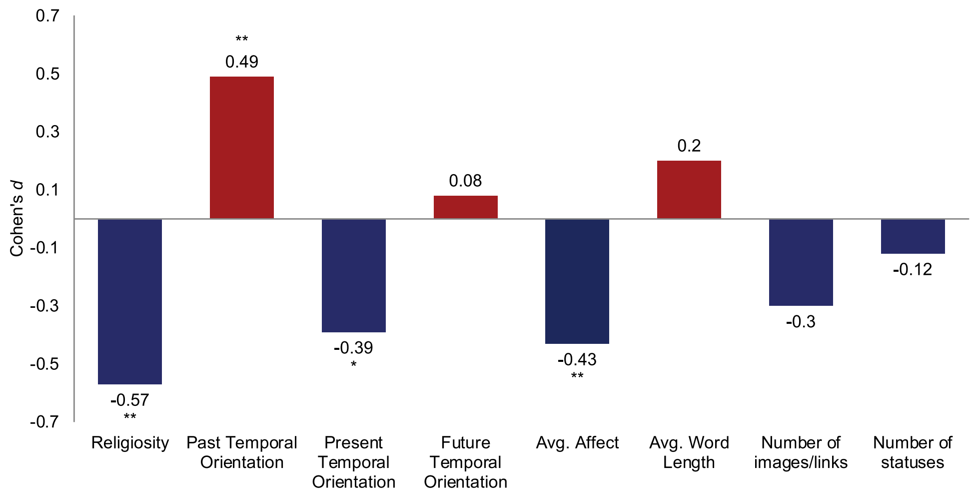

Figure 3. Features predicting SUD treatment retention versus discontinuation at 90 days. Theoretical factors and meta-linguistic features of the SUD treatment outcomes at 90 days were present. The negative Cohen's *d* values represent the protective factors for SUD treatment retention, and the positive Cohen's *d* values represent the risk factors for SUD treatment discontinuation. *** $p < .001$, ** $p < .01$, * $p < .05$. Language source: Facebook language.

habits of time expressions (e.g., "yesterday" and "next week"), which are not simply interchangeable with the attitudes and cognitive styles measured by self-report surveys. Perhaps, individuals with a present temporal perspective might have difficulties in developing long-term plans (43,51), while, talking and writing about the present lead people to enjoy the moment without being trapped by the past distress or future uncertainties and to engage with the environment (43), which helps them remain in the SUD treatment programs.

Other important language features could also help us to understand treatment retention and discontinuation. For example, the use of articles refers to concrete and impersonal objects or events, which has been previously found to reflect the stylistic characteristics in speech and individuals' attitude toward the world (92). In the research which correlated word use from the 1-h life history interview with self and acquaintance personality ratings and behavior, it has found that individuals who used more articles were more philosophical, skeptical, and open to experience (have broad interests (93)). Similarly, a diary analysis found that the higher percentage of articles participants used was correlated with less immediacy of the language, lower agreeableness and higher openness to experience in their personality, and with less participation in the classroom (92). Though we do not have a direct link between the use of articles and health-related behaviors, previous research has demonstrated that marijuana users scored low on agreeableness and high on openness to experience (94), which might indicate the link between the high percentage of article use and SUD treatment discontinuation. We also attempted to extract the context for the high-frequency topics associated with SUD treatment discontinuation. Interestingly, these topics covered diverse domains, including many aspects of their life. These findings reveal that people who succeeded in this treatment program are more homogeneous than people who left treatment prematurely. Future explanations of this difference need more empirical studies and observations in clinical settings.

The current study has limitations. First, our final sample size is relatively small and participants were excluded due to limited access to social media accounts or insufficient Facebook language data. So generalization of our findings to broader clinical populations (e.g., non-Facebook users) should be cautious and needs more investigations in larger samples. Active social media users in SUD treatment-seeking populations may be better targeted by our linguistic analysis methods. Second, different treatments vary in type and intensity of services. Our language markers of treatment retention may or may not also be effective in other types of treatment programs and are worth further exploration. Third, to be accurate, the retention in our study cannot be fully equal to staying in the SUD treatment. We use "survey retention" as a proxy for "treatment retention" because of our limited access to fine-grained treatment retention data. We believe this could closely represent the actual treatment outcomes with our on-site data collection assistants who tried to reach out to patients when they discontinued our survey. Using our survey-based outcomes also allowed us for consistent reporting across treatment facilities. Future studies should also consider actual medical records to improve accuracy. Fourth, we only include English data in analysis to achieve the best performance of the machine learning models, as most of which are developed based on English (e.g., LDA topics).

Extending our findings to non-English contexts should be cautious. In addition to language, many other factors could also impact SUD treatment outcomes. Individuals with the sets of linguistic markers of SUD treatment retention may share some similar social-psychological qualities and are more likely to be adherent to the SUD treatment. As language could reflect and be shaped by one's psychology and experience, we encourage future research to explore other mechanisms that may influence language use and SUD treatment (e.g., characteristics that are associated with SUD treatment). Also, we only used the pre-treatment language, future studies could include the language used during the treatment to see if the language used before and during treatment will make differences in treatment outcome correlations.

The current study suggests the importance of introducing AI-based language analysis into traditional psychology and SUD research. For the first time to our knowledge, we identified language flags signaling SUD treatment outcomes and confirmed the literature on protective and risk social-psychological factors linking to SUD treatment in language. Utilizing novel methods of extracting and analyzing big data using Natural Language Processing can lead to major advancements in current SUD treatment research (1): early indicators of treatment outcome can be identified via language markers before patients enter treatment, and (2) incorporating these markers in practical guides could help counselors, psychiatrists, and other health workers to characterize patients and tailor treatment plan to improve the intervention outcomes.

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The corresponding author, Dr. Brenda Curtis, had full access to all the data in the study and took responsibility for the integrity of the data and the accuracy of the data analysis.

Author contributions

Tingting Liu: Methodology; Data analysis; Visualization; Literature review; Manuscript draft preparation, editing, and reviewing; Salvatore Giorgi: Conceptualization; Methodology; Data analysis; Manuscript editing and reviewing; Kenna Yadeta: Literature review; Manuscript draft preparation and editing; H. Andrew Schwartz: Conceptualization; Project administration; Methodology; Manuscript editing and reviewing; Lyle H. Ungar: Conceptualization; Project administration; Methodology; Supervision; Manuscript editing and reviewing; Brenda Curtis: Conceptualization; Funding acquisition; Project administration; Methodology; Supervision; Manuscript editing and reviewing.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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