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Language Models Learn Sentiment and Substance from 11,000 Psychoactive Experiences

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Abstract

Drugs like entactogens and psychedelics appear poised to enter clinical psychiatry, however we lack a unified framework for quantifying the changes in conscious awareness optimal for treatment. We address this need using transformers (i.e. BERT) and 11,821 publicly-available, natural language testimonials from Erowid. First, we predicted 28 dimensions of sentiment across each narrative, validated with clinical psychiatrist annotations. Secondly, another model was trained to predict biochemical (pharmacological and chemical class, molecule name, receptor affinity) as well as demographic (sex, age) information from the testimonials. Thirdly, canonical correlation analysis (CCA) linked the 52 drugs' affinities for 61 receptor subtypes with word usage across the testimonials, revealing 11 latent receptor-experience factors each mapped to a 3D cortical atlas of receptor gene-expression. Together, these 3 machine learning methods elucidate a neurobiologically-informed, temporally-sensitive portrait of drug-induced subjective experiences. These models are mutually confirmatory, pointing to an underlying structure of psychoactive experience dominated by the distinction between the lucid and the mundane, but also sensitive to effects unique to individual drugs. For example, MDMA was singularly linked to mid-experience swelling of "Love", potent psychedelics like DMT, and 5-MeO-DMT were associated with "Mystical Experiences", while other tryptamines were associated with an emotional constellation of "Surprise", "Curiosity" and "Realization". Applying these models to real-time biofeedback (e.g. EEG, or MRI) with zero-shot learning that tunes the sentimental trajectory of the experience through changes in audiovisual outputs, practitioners could guide the course of therapeutic sessions, maximizing benefit and minimizing harm for patients.

Significance Statement

Research suggests that both the *quality* and the temporal *trajectory* of acute psychoactive experiences shape their therapeutic impact. Existing psychiatric medications like antidepressants and antipsychotics will inevitably be used with novel psychoactives, yet we lack a unifying paradigm to describe how these drugs impact subjective experience. Natural language testimonials are a rich source of this information. Mining testimonials with language models, like transformers, we detect sentimental and demographic information, monitor its development over time, and localize it to specific brain regions. This framework maps a huge set of 11,821 experiences from a diverse group of 52 drugs into a unified space. Frameworks like this can inform treatment strategies for optimizing both existing and novel psychotropic medications.

Main text

Introduction:

Human sentiment is a critical yet elusive measurement to obtain. This is especially true for therapeutic psychedelic experiences, where the subjective emotional content of a trip correlates with clinical efficacy (1). Drug-induced experiences such as overwhelming feelings of love, ego-dissolution, and mystical union with the environment all correlate positively with the treatment of depression (2). Similarly, conventional psychiatric medications like antidepressants and antipsychotics target distinct but overlapping ranges of subjective experience (e.g. anhedonia, anxiety, or hallucination). As novel molecules are introduced into standard psychiatric practice it is essential to establish a unifying paradigm–a rosetta stone–which translates how different drugs modulate neurochemistry and subjective experience (3). Machine learning can assist in this translation by revealing latent structures that link phenomenal and biochemical levels of drug experience (4).

Despite their fundamental role in human affairs, scientists lack a consistent neurobiological basis for emotion (5). While core aspects of emotion such as arousal and hedonic tone appear conserved in our species, the diverse subjective manifestations of both psychiatric illnesses and drug-induced experiences require more nuanced, multi-dimensional classifications (6). Recent advances in Natural Language Processing (NLP) have operationalized this ambiguity by providing taxonomies of emotion derived from vast datasets of text that have been manually annotated (7–9). Simultaneously, transformer-based models have made great progress on many language tasks, and are increasingly able to learn general representations applicable to many domains (10–12). In this paper, we use models that have been pre-trained on the

sentiments found in movie reviews and reddit posts to estimate and disentangle emotional affect as described in testimonials from drug experiences (7).

Emotional landscapes unfold in time. This temporal trajectory of sentiment is of great significance; it is literally the substrate in which significance is felt. Moreover, the shape of a sentiment's trajectory shapes the memory that is formed. For example, the peak-end rule states that the intensities of the peak and the end of an experience are what determine the depth of its imprint in memory, and that intervening periods, regardless of their duration, are liable to be forgotten (13). As a consequence, the intensity of the experienced emotion can be distinct from the emotion remembered. This has led some researchers to draw a distinction between the *experiencing-self* which is involved in direct, embodied experience, and the *remembering-self* that recalls and integrates such experiences into a unified, autobiographical narrative (14, 15). The testimonials of drug experiences examined here give insight into both of these aspects of self. While authored after-the-fact by the remembering self, most include a minute-by-minute and hour-by-hour timeline that chronologically reconstructs what the experiencing-self felt in each moment.

However, it is questionnaires, not testimonials, which typically serve as clinical trial endpoints for psychiatric interventions. By evaluating psychoactive experiences on the whole, at their end, questionnaires privilege the remembering-self. Furthermore, the vast range of psychoactive experiences are compressed to scalar values assigned to a few aspects of the experience (e.g. 14 for Hamilton Anxiety Scale (16), 30 for the Mystical Experience Questionnaire (17, 18)). These metrics reduce the rich sentimental trajectories through time of drug experiences to low-dimensional points in a space spanned by the researcher's conceptual priorities, rather than those of the patient.

Here we show how combining free-form testimonials with large-scale language models allows the simultaneous quantification of multiple sentiment trajectories that occur throughout a trip. This high-dimensional representation–learned from more than 50 drugs and over 11,000 trips–registers a cacophony of pharmaceuticals into a single unified space of psychoactivity. This enables rigorous comparisons across drug-classes, indications, and mechanisms of action. Combining these representations with zero-shot learning will open the door to the precise and on-demand engineering of psychoactive experiences (19).

Results:

We amassed a corpus of 11,821 psychoactive experiences from Erowid, which we semantically and chemically characterize with two supervised BERT-based models, and

one Canonical Correlation Analysis (CCA). The first model, BERTowid, is trained using multi-task, multi-label, supervised-learning directly on Erowid testimonials. BERTowid is trained to “read” a 512 token excerpt from the testimonial and predict the associated drug, its chemical and pharmacological class, self-reported gender and age, 52 metadata tags and 11 canonical correlation component weightings and 30 receptor affinities. The second model, BERTiment, is trained to detect 28 sentiments simultaneously on a corpus from Reddit (7). Using transfer-learning, it then makes inferences on Erowid revealing sentimental trajectories which validate expected emotional associations and are consistent with pharmacological groupings. Both models generalize to unseen data, demonstrating how machine learning on crowd-sourced, noisy, publicly-available semantic data can lead to diverse biochemical inferences.

This point is reinforced by our findings from CCA which identified a latent structure of 11 components mapping between the semantic data and the receptor affinity profiles of each drug (4). CCA is a linear model and relies on a bag-of-words representation of the entirety of the testimonial text, while the transformers are deep nonlinear neural networks which positionally-encode a subset of text excerpted from the testimonials. Despite the large differences in representation and model, BERTowid is able to directly learn and infer the CCA weightings, while many of the BERTiment emotion-scapes reveal similar drug weightings as the most prominent components from CCA, see Figure: Dynamic Time Warp Distance Between Emotions Supports CCA 0.

BERTowid

There is noise inherent in any crowd-sourced, open, anonymous dataset like Erowid, which includes reports from many illegal substances rife with potential impurities, misrepresentations from disreputable distributors, and non-standard dosages. Nonetheless, BERTowid shows powerful discrimination at several different granularities of pharmacology, classifying amongst 52 drugs, 22 ligand chemical types, and 10 pharmacologic classes with mean test set accuracies of 53%, 64% and 78%, respectively. Furthermore the mistakes the model makes are consistent with expected biochemical and pharmacological classifications. For example, the two large biochemical classes of psychedelics–phenethylamines and tryptamine–are much more likely to be mistaken for each other, than for a benzodiazepine, antidepressant, or opioid (see confusion matrices in Figure: Drug Classification Performance). Additionally, despite uneven ascertainment, 35 of the meta data tags have predictive power, with some of the best performing tags being “Medical Use”, “Mystical Experiences”, “Alone” and “Addiction Habituation”, with areas under the receiver operating characteristic curves (ROC AUC) ranging from 0.88 to 0.95, areas under the precision-recall and ROC curves for all tags are shown in Figure: Results. Tags with less than 150 testimonials, like “Military” and “Pregnancy Baby” were not convincingly learned.

Some testimonials include self-reported age (3,116) and gender (11,129) with which we trained gender-classifying (ROC AUC 0.85) and age-regressing (Pearson correlation 0.56) output heads. Despite the missingness and class imbalance in these labels, our ability to predict age and gender from these reports is evidence that demographic information is contained within the testimonials. Accurate detection of sensitive features, such as gender and age, is a critical first step towards de-biasing predictions through iterative removal of confounded subspaces (20, 21). Given their potential role in healthcare, the ability to apply these models without bias is of utmost importance.

BERTowid test set performance on the CCA components (described below) drops off almost exactly with their importance ordering, with (Pearson correlations ranging from 0.68 for CCA 0 to 0.24 for CCA 11). This indicates that components which explain more of the variance between testimonials and affinities also tend to be more effectively learned. Through an entirely different analytic paradigm BERTowid appears to broadly confirm the salience and ranking of the 11 CCA components described below.

Repeated inference with BERTowid over contiguous windows of text in held-out testimonials followed by interpolation constructs the trajectories shown Figure: Trajectories. Confirming its reputation as the “spirit molecule”, DMT displayed heightened predicted trajectories for both “Mystical Experiences” and even more dramatically for the tag “Entities and Beings”, echoing themes uncovered in manual DMT-specific analyses (22). As expected, the Depression tag trajectory highlights antidepressants, while the “Addiction Habituation” tag is consistently elevated for the stimulants cocaine and methamphetamine.

BERTiment

BERTiment is trained to predict 28 emotions as binary classifications based on annotations from Reddit (7). All emotion predictions generalize to unseen data with ROC AUCs ranging from a low of 0.72 for “Realization” to a high of 0.97 for “Love”. BERTiment is further validated by training a hedonic tone classifying BERT-based model with positive and negative movie reviews from IMDB (9). BERTiment and the IMDB-trained classifier infer emotion predictions on the entire Erowid dataset. Figure: Results Panel J shows correlations between all 28 emotion predictions and the IMDB positive vs negative classifier. The signed Pearson correlations between their predictions neatly sorts the fine-grained emotion taxonomy by hedonic tone. The emotions “Admiration”, ”Pride”, “Approval”, “Love”, and “Joy” have the highest positive correlations, while “Annoyance”, “Nervousness”, “Embarrassment”, “Disapproval”, and “Disgust” have the largest negative correlations. Despite originating from entirely different datasets (i.e. movie reviews and Reddit posts) these models have learned

representations of sentiment that are mutually reinforcing, albeit at different levels of granularity. To ease comparison between different drugs and chemical classes we use this hedonic-tone ordering for all “emotion-scapes” (Figure: EmotionScapes).
In addition to this cross-dataset validation, we also conducted expert human validation. A clinical psychiatrist manually adjudicated 310 emotion-tags from 200 Erowid excerpts. Concordance between the model and the psychiatrist was well within the range of inter-human variability as reported in the original GoEmotions paper (7). Specifically, human labeled emotions were in the top 10 BERTiment emotions for 87% of the labels, in the top 5 for 73%, and in the top 1 for 38%, see Figure: Results, Panel I.

Qualitative manual inspection confirms that the most extreme (both positive and negative) predictions for each sentiment task were prominent examples of the emotion (or its opposite), see Table: Extreme BERTiment. As expected with extreme language, profanities, capitalization and modifiers like “very” and “so” are common. To quantitatively evaluate the sentimental trajectories, BERTiment made inferences across all time points and all testimonials. For comparison, the inferred emotional trajectories were interpolated to the mean sampling frequency of the testimonial (see Figure: Trajectories for many examples). Dynamic Time Warping (DTW) measured the distance between the averaged trajectories for each emotion and each pharmacological and biochemical class (23). To achieve a comprehensive view of the emotional trajectories we create cross-drug DTW distance matrices where each cell contains the DTW distance between the drug (or drug class) in the row and in the column. We use a signed distance which is positive (shown in red) if the mean sentiment prediction of the row’s drug is higher than that of column’s drug and negative (shown in blue) otherwise Cross-drug DTW distance matrices and sentimental trajectories are shown in Figure: Compare Trajectories with Dynamic Time Warps. The DTW reveals emotional landscapes that conform to expectations based on prior research into pharmacological classifications, molecular structure, as well as questionnaire-based research (and anecdotal reports) that have described the phenomenology induced by diverse compounds (24, 25).

For example, the “Love” trajectory for MDMA starts high and ends higher – fitting for a drug colloquially known as the “love-drug”. This arc is clearly distinguished from all other drugs, though closely tracked by the related entactogen, MDA, see Figure: MDMA is Singular. The “Sadness” trajectories of the stimulants (cocaine, amphetamine, and methamphetamine) are tightly coupled and rise gradually over the course of the testimonial, while the antidepressants (paroxetine, venlafaxine, and sertraline) start much higher than the stimulants but gradually fall. In contrast, the stimulants and antidepressants start with similar “Anger” levels, but over the course of the report

methamphetamine and cocaine rise dramatically while for antidepressants they increase somewhat less, see Figure Trajectories.

The emotions “Realization”, “Curiosity”, “Confusion”, “Surprise”, and “Amusement” are consistently elevated in subjective testimonials of hallucinogens and psychedelics as compared to other drug classes, most notably the opioids. This constellation of emotional trajectories provides additional discernment within the broad, overlapping classes of hallucinogens and psychedelics as shown in Figure: Psychedelics are Curious. For example, Salvia and DMT are both high in “Realization”, and “Curiosity”, however Salvia triggers more “Confusion”, while DMT generates more “Surprise”. PCP in contrast is high in “Confusion” and “Amusement”, but lower in “Realization”, “Surprise” and “Curiosity”. The opioids are consistently lower in all of these emotions, but “Relief” provides an interesting counterpoint, as it is higher in opioids than in hallucinogens or psychedelics, which one would expect for drugs widely prescribed for their pain-*relieving* effects. Notably, not every emotion clearly distinguishes the drugs, the emotions “Neutral” and “Optimism” are quite conserved across pharmacological classes. For every drug analyzed, “Neutral” decreases as the testimonial proceeds, while “Optimism” trajectories for every drug increase dramatically near the end, resembling a ski-jump, see Figure Optimism and Neutral Trajectories. As if the peak-end rule is a self-fulfilling prophecy, testimonials for all drugs tend to end on an optimistic note. The reduction in “Neutral” over the course of a trip is consistent as drugs effects reveal themself to the user over time, a similar reduction in neutral sentiment over the course of a narrative was shown in (26).

Canonical Correlation Analysis

By aggregating a diverse assortment of drugs from distinct pharmacologic classes, we aimed to illuminate latent principles that organize diverse psychotropic states of consciousness. For this purpose, we have charted regularities across a large corpus of naturalistic drug experiences. Our pattern-learning strategy discovered a series of discrete components that integrate subjective descriptions with the unique neurotransmitter affinity fingerprint of each psychoactive drug. The receptor gene expression distribution was spatially unique for each component, spanning the higher association cortices and unimodal sensory cortices. The dominant factor described a vector characterized by *lucid-beauty* on one extreme and *mundane-suffering* at the opposite extreme. The second and third most explanatory factors contained poles of *depression-insomnia* and *impulsivity-addiction* contrasted with *perception-celebration* and *cosmic-expansion*, respectively. In this way, we have deconstructed the changes of conscious awareness triggered by a diverse array of psychoactive compounds into component parts.

Although not imposed by our analytic model, the cortical mappings of factors often turned out to be spatially contiguous with smooth transitions of expression strength between neighboring

brain regions. These mappings respected well-described anatomical and functional divisions and were often found to be mirrored in homologous brain regions in the left and right hemispheres. These observations are noteworthy because all steps of our modeling pipeline were blind to brain regions and are informed only by receptor affinities and natural language.

The dominant component (Figure: CCA 0) explained the largest portion of joint variation between receptor affinity profiles and word-usage frequencies. This central component isolated a semantic theme characterized by abstract, transcendental terms such as *reality, universe, everything, consciousness,* and *peak* as well as a constellation of perceptual phenomena including *visuals, patterns, music,* and *sound*. These terms were linked to drugs DMT, LSD, and psilocin, as well as mostly serotonergic receptor affinity at 5-HT2A, 5-HT1A, 5-HT2C, and the expression of these receptors in the medial prefrontal cortex. The opposite extreme of this factor flagged words that describe a theme of mundane suffering: *depression, pain, addiction, sleep, awake, daily, weeks, months, work, and anxiety.* This latter theme was linked to drugs cocaine, amphetamine, methamphetamine, and oxycodone, as well as receptor affinity at MOR, DOR, NET, and DAT, while the expression of these receptor genes was densest in the posterior cingulate cortex and the inferior parietal lobule. Notably, this component evoked a similar structure found by the BERTiment model for 17 of its 28 emotions, see Figure: Dynamic Time Warp Distance Between 17 Emotions Supports CCA 0.

The eleven significant components reveal latent patterns of correlation between drug receptor affinity and word-usage from subjective testimonials. Each is traced to specific cortical sites using receptor RNA expression as measured by invasive tissue probes, building on prior research (4) by incorporating more substances and testimonials. For example, the dominant component, CCA 0, *lucid-beauty* and CCA 2, *cosmic-expansion,* localized gene expression for canonical hallucinogenic 5-HT2A and KOR receptors (27) to high-level integration hubs like the medial prefrontal cortex, dorsal anterior cingulate cortices, and temporoparietal junction. In contrast, the opposite extremes of the same components (*mundane-suffering* and *perception-celebration*, respectively) instead emphasized somatic and perceptual phenomena, linked to the drugs cocaine and MDMA, associated with receptor expression in the visual and primary sensory cortices. A plethora of similar patterns linking drug, receptor affinity, subjective-experience, and large-scale functional brain networks were revealed across the 11 receptor-experience components, described in detail in Figure: CCA 0 - Figure: CCA 10.

Convergences Between BERTiment, BERTowid, and CCA Components

Remarkably, the three distinct ML approaches spanning supervised-learning in BERTowid, transfer-learning with BERTiment, and self-supervised (or arguably unsupervised) learning with CCA elucidated similar findings. MDMA was found to elicit a uniquely positive palette of affective attributes (see Figure: MDMA is Singular) that are of particular interest given its apparent efficacy as a treatment for PTSD (28). At the most positive extreme of the IMDB-derived spectrum of hedonic tone, MDMA was ranked highest among all 52 compounds for “Admiration”, “Pride”, “Approval”, “Love”, “Excitement”, and “Gratitude”, and was only narrowly edged out by opioids for “Joy” (Figure Emotion-Scapes). Perhaps due in part to their

unique subculture of recreational use (29), BERTowid tag weightings for entactogens (Figure Tagscapes) exhibited heightened levels of festivity and dancing, but also relational, emotional, and effusive, (e.g. “Glowing”) phenomena. Using CCA to incorporate its receptor-affinity fingerprint, MDMA was most closely linked with receptor-experience patterns highlighting *perception-celebration* and *emotional-extremes*, with receptor gene-expression in the visual and primary sensory cortices.

Results also show important distinctions *within* and *between* psychedelic subclasses. In particular, the tryptamines exhibit elevated levels of “Curiosity”, “Surprise”, and “Realization”, while phenethylamines highlight relatively higher levels of “Admiration”, “Excitement”, and “Gratitude”. Of note, tryptamines–especially potent, short acting DMT and 5-MeO-DMT–overall had higher “Mystical Experiences” tag weightings than the phenethylamines like mescaline and 2-CE. Interestingly, the chemically distinct diterpenoid compound Salvinorin A shared with these prototypical tryptamines high levels of “Surprise”, “Curiosity”, and “Realization”, in addition to a very high ranking of “Mystical Experience”. These crucial overlaps and divergences between different chemical subclasses hint at complex structures of emotion that may undergird clinically relevant experiential parameters such as mystical experiences.

Drug factorization in the central CCA component aggregated stimulants (including MDMA) and psychiatric medications into one pole, and associated them with phenomena relating to suffering, addiction, and the mundane. Using an entirely separate analytic pipeline, BERTiment DTW charts demonstrated that these same drugs all ranked highest for a constellation of emotions compatible with this CCA theme such as “Disappointment”, “Grief”, “Annoyance”, “Disapproval”, “Disgust”, “Sadness”, and “Anger”. The opposite pole grouped psychedelic and hallucinogenic drugs together with terms highlighting a theme of abstract, lucid, and beatific phenomena. BERTiment DTW found these drugs to have much higher scores for “Curiosity”, “Admiration”, “Amusement”, “Surprise”, and “Realization”. This dichotomy between the gloomy, prosaic, quotidian aspects of human sentiment and the more abstract, expansive, and creative aspects of human potential was judged by the CCA to be the most explanatory distinction in this large corpus of drugs, and the majority of sentiment dimensions fit neatly into the same schema (Figure: Dynamic Time Warp Distance Between 17 Emotions Supports CCA 0).

Discussion:

Both linear CCA and nonlinear transformers, supervised or self-supervised, models can learn to map a diverse array of drug experiences into a unified, biochemically-informed, high-dimensional space. Using only natural language, this space can predict information like the intensity of mystical experience or the depth of grief: qualities of subjective experience that are of great clinical import when assessing psychiatric drug efficacy. Applying these models sequentially on retrospective reports creates evocative narrative trajectories which reflect pharmacological distinctions and confirm many anecdotes from drug subcultures. The peak-end rule inspired us to look for these trajectories, but the peak-end rule has nuances and exceptions; it is a rule not a law. For example, if pleasure is increasing or decreasing when an experience ends can be more important than the peak level of pleasure felt (30). The shapes of

the trajectories produced by BERTowid and BERTiment can capture these nuances in ways that a single questionnaire, which evaluates the experience as a whole, cannot.

While the trajectories we constructed unfold over the narrative language in the trip report, the methods we describe could naturally apply to other streams of phenomenological and neurochemical data. Modalities as diverse as EEG, ECG, MRI or real-time audio and video of psychoactive experiences are amenable to the trajectory construction described here, simply by replacing the BERT encoders with appropriate pre-trained encoders (e.g. a 1D CNN for EEGs or ECGs (31, 32)). Excitingly, such modalities can collect data in a manner which mitigates the issues inherent in open and anonymous datasets like Erowid, such as uncertainty about duration and dosage. Any of these complementary, parallel data streams mentioned would provide a standard sampling rate for the entire experience, and controlled clinical administration would ensure precise purity and dosage.

However, given the subjective quality of the clinical endpoints for many psychiatric interventions, we contend that the high-resolution objective data obtained from something like an EEG will offer complementary but not identical information as that found in the subjective richness of natural language testimonials. Combining real-time datastreams with the zero-shot learning capability of transformers, it is possible to envision a future of personalized, responsive psychoactive experiences. Music appreciation, for example, has been shown to be enhanced by certain psychedelics (33). What if therapists could monitor the emotional palette as it is felt, programmatically tweaking the experience to maximize appreciation?

Going beyond just appreciation, the tables of extreme predictions from our models make clear that transformers learn semantics reflecting both the training label as well as its opposite meaning. Word2Vec showed that directions, not just points, are meaningfully encoded in latent spaces of natural language; (e.g. King-Queen = Man-Woman) (34). Perhaps the directions connecting both extremes of “Love” or “Mystical Experience” learned here can be used to guide a trip as it unfolds. Psychedelic therapists of the future may use AI to help their patients navigate the latent spaces of subjective experience towards psychoactive journeys of minimal risk and maximal therapeutic benefit.

Materials and Methods:

Several diverse datasets were brought together in this study, namely the Erowid dataset of 11,821 drug testimonials (35), 61 receptor affinities for 44 drugs from the Psychoactive Drug Screening Program (PDSP) (36), augmented with affinities for the8 phenethylamines from (37), RNA gene expression data for 200 brain regions from the Allen Brain Atlas (38) and 210K reddit posts with 28 human annotated human emotions (7). The 10 pharmacologic classes and the 22 chemical classes were retrieved from the Psychonaut Wiki (39).

Data Preprocessing for Transformers

Scraped testimonials were parsed for meta data, drug-masked, and tokenized. Drug-masking removed all occurrences of drug names in the testimonial text, including slang and common misspellings. See code for the full list of masked words. Models were initialized with pre-trained weights for the base BERT encoders. All model weights are publicly available and can be downloaded from tensorflow hub. Except when otherwise noted, the base BERT model used was trained with the Stanford Sentiment Treebank data (26) and is available at (https://tfhub.dev/google/experts/bert/wiki_books/sst2/2) with the preprocessor (tensorflow/bert_en_uncased_preprocess). The pooled output from the base BERT model was extended with a dropout layer (40) followed by a dense layer for each task (e.g. BERTiment has 28 distinct outputs–one for each binary emotion classification).

Testimonials vary in size, while the input to BERT models is at most 512 tokens. A sliding window inference step allowed all available data to be used and created prediction series of varying lengths for each testimonial from each model. Different window sizes are compared in Figure: Word Window Size Comparison. When the window size exceeds the testimonial size input is zero-padded. When the window size is smaller than the testimonial size the testimonial is split into contiguous blocks of text and the model is applied to each one. This is how the trajectories of both BERTowid and BERTiment are constructed.

BERT-based model encoder fine-tuning

The encoder backbone of both BERTowid and BERTiment is a bidirectional transformer (BERT) trained with a masked language model objective. Inspired by the Cloze tasks (41), BERT is trained to use both the left and right context to predict a masked word or token (11). These models can be transferred simply by adding output layers which take the BERT encoder representation as input and fine-tune it for new tasks. This is the approach taken by both BERTowid and BERTiment. The encoder backbone contains 109 million parameters. Pretrained weights from different corpus have been published. BERTowid results with weights from the original BERT paper as well as from google experts SST2 are compared in Figure: BERT Encoder Weights Comparison showing similar performance. Prior to the output layer for the fine-tuning task, we also insert a dropout layer and use a dropout rate of 0.5 (40). Experiments with different dropout rates are shown in Figure: Dropout Rate Comparison. The ADAMw (42) stochastic gradient descent optimization procedure updates model parameters. It is initialized with a learning rate of 1e-5 and a batch size of 32 text excerpts. The models are trained for 16 epochs and weights with the minimum validation loss are serialized for downstream comparison and inference.

Training BERTowid

The Erowid metadata, the inferred CCA weights and the receptor affinities from PDSP provide a diverse training labels for BERTowid, each with various tradeoffs. Both classification (e.g. drug, tag, gender) and regression tasks (e.g. age, affinity, CCA weights) are considered. All classification tasks are trained to minimize a cross entropy loss, while regression models are trained to minimize the mean squared error of their predictions. Cross entropy and squared error are categorically different values. Mixing them in a single model requires a term to balance between the two kinds of loss. Optimization was found to be sensitive to this value, requiring careful tuning to avoid convergence for only one of the loss types. To mitigate this, the multitask BERTowid is trained and serialized separately for classification and regression tasks.

Many of the categorical labels are class-imbalanced. This imbalance leads to poor performance on the less well-represented drugs and tags. To mitigate this we considered a weighted cross entropy loss, which scaled the loss by the inverse of each labels' prevalence to compensate for the imbalance. As Figure: Cross Entropy Class Imbalance Weighting shows, the weighted loss did increase precision for less well represented drugs (at the cost of reduced precision on the more prevalent drugs). However, the results for tags were less convincing with only minor improvements in precision for the 4 rarest tags. A likely explanation is that less common tags are in fact less informative and may be applied less rigorously or consistently by the Erowid moderators. Giving these less informative labels more weight in the loss function results in a worse model. With a window size of 64 words and all categorical tasks, 16 epochs takes about 3 hours on a NVidia V-100 GPU.

Training BERTiment

The BERTiment training procedure is discussed in detail in the GoEmotions paper (7). Our approach only differs in dropout rate, 0.5, learning rate, 1e-5, and batch size, 32, where for consistency we used the same hyper-parameters and base model used to train BERTowid. The GoEmotions data contains about 58K Reddit posts and 28 emotion annotations, it can be downloaded here. We split the data 70-20-10 between training, testing and validation sets. The 28-head BERTiment is trained for 16 epochs which takes about 2 hours on a NVidia V-100 GPU. Validation loss is assessed at the end of every epoch and the model with minimum validation loss is serialized for downstream analyses.

Canonical Correlation Analysis

The CCA mapping between testimonials and affinities is described in detail in the Trips and Neurotransmitters paper (4). The approach here only differs in the size and provenance of the data used. We extend from 27 drugs to 52, from 40 receptor subtypes to 61, and exclusively source affinity values from the PDSP or (37). Additionally, affinity values are restricted to experiments with human proteins and aggregated in a hot-ligand sensitive manner. CCA was used to chart patterns of correlation between word-usage frequencies in drug testimonials and receptor affinity profiles. Each of these receptor-semantic components were composed of two poles of a weighted list of words and a weighted list of receptors. The receptor weights for each component were mapped to the cortex using Allen Brain Atlas receptor RNA expression quantities measured by invasive tissue probes.

Scientific Computing Implementation

Python was selected as the scientific computing language to capitalize on its open-source ecosystem which helps enhance replicability, reusability, and provenance tracking. The Tensorflow deep-learning framework was used for the transformer models and the ML4H tools were used for model evaluation (43). The Dynamic Time Warp implementation was provided by the fastdtw python package (https://pypi.org/project/fastdtw/ (44)). The scikit-learn package provided efficient, unit-tested implementations of the CCA algorithm (http://scikit-learn.org). This general-purpose machine learning library was interfaced with the nilearn library for design and efficient execution of brain imaging data analysis workflows (http://github.com/nilearn/nilearn). Data plots were generated by Matplotlib (https://github.com/matplotlib/matplotlib). Trained models will

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Figure Legends

Figure: Pipeline

An overview of the study showing data sources, models and a selection of key results. Natural language data from Rotten Tomatoes and Wikipedia was used to pre-train the base BERT model, and the IMDB movie review dataset was used to validate BERTiment. BERTiment was trained with Reddit posts annotated with 28 emotions. BERTowid was trained with Erowid testimonials, metadata, PDSP affinities, and the weights output by CCA. CCA was performed on the Erowid dataset and neurotransmitter receptor affinity from the PDSP. CCA found 11 statistically-significant components which BERTowid was also able to learn. Both BERTowid and BERTiment generalize to unseen data and can be used to build trajectories that describe the emotional and semantic landscapes of psychoactive experiences.

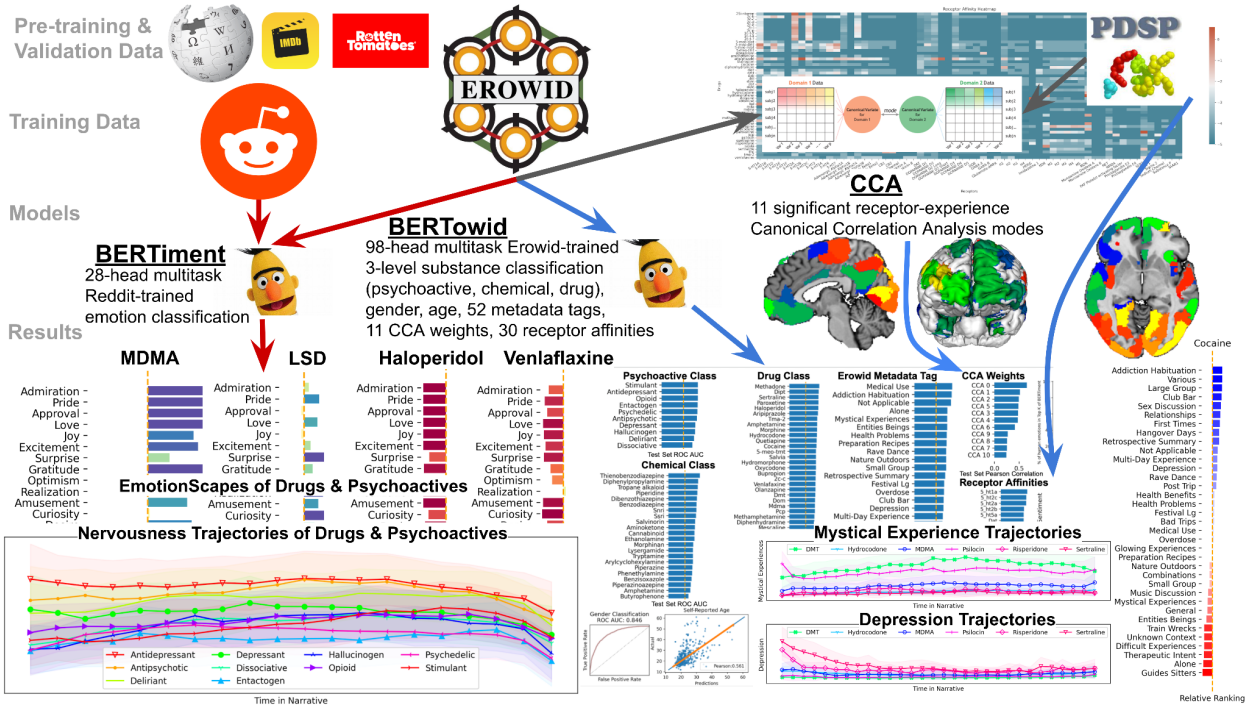


Figure: Results

BERTowid multitask evaluation on held-out test data and BERTiment comparison with clinical psychiatrist emotion adjudications and generalization to hedonic tone on Erowid testimonials. BERTowid classifies drugs at 3 different levels, amongst the 10 pharmacologic classes (A), 22 chemical classes (B), and the 52 drugs included in the study (C). The ROC AUC for the 35 meta tags with positive examples > 150 are shown in the third column (D). Test set Pearson correlation of the 11 CCA weight predictions (E) and the 30 receptor affinities (F) are shown in figure 4. The ROC curve for self-reported gender (G), and the scatterplot for self-reported gender (H) are shown in the bottom left. BERTiment evaluations are in the rightmost column with comparison with psychiatrist adjudicated emotions top right (I), and Pearson correlation with hedonic tone prediction on the Erowid dataset from the IMDB trained positive sentiment BERT classifier (J) at bottom right. The emotion ordering given by the hedonic tone classifications are used in Figure: Emotion-Scapes.

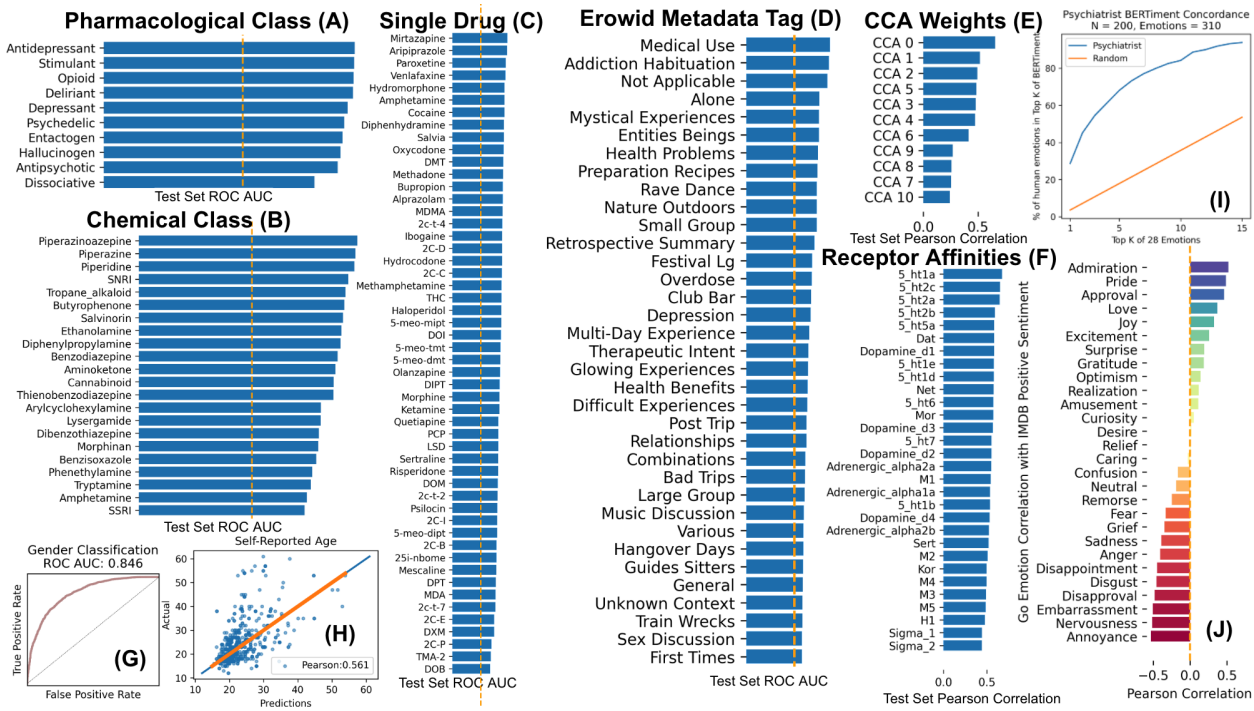


Figure: Trajectories

Applying BERTowid (left plots) and BERTiment (right plots) in a sliding window across each testimonial followed by linear interpolation gives the psychoactive trajectories shown here.

Each trajectory corresponds to one of the model's output heads. The first row shows the "Addiction/Habituation" trajectory from BERTowid and the "Anger" trajectory from BERTiment, note how the stimulants cocaine and methamphetamine correlate with each other and between the models. This convergence is even clearer in the second row with BERTowid's "Depression" tag and BERTiment's "Sadness" label. Antidepressant testimonials start high in both and trend down, while stimulants start much lower but trend upward. Rows 3 and 4 show how the Erowid tags of "Mystical Experience" and "Entities Beings" flag the "spirit" molecule, DMT, while the emotions "Love" and "Approval" highlight the "love" drug, MDMA, as well as the related entactogen, MDA.

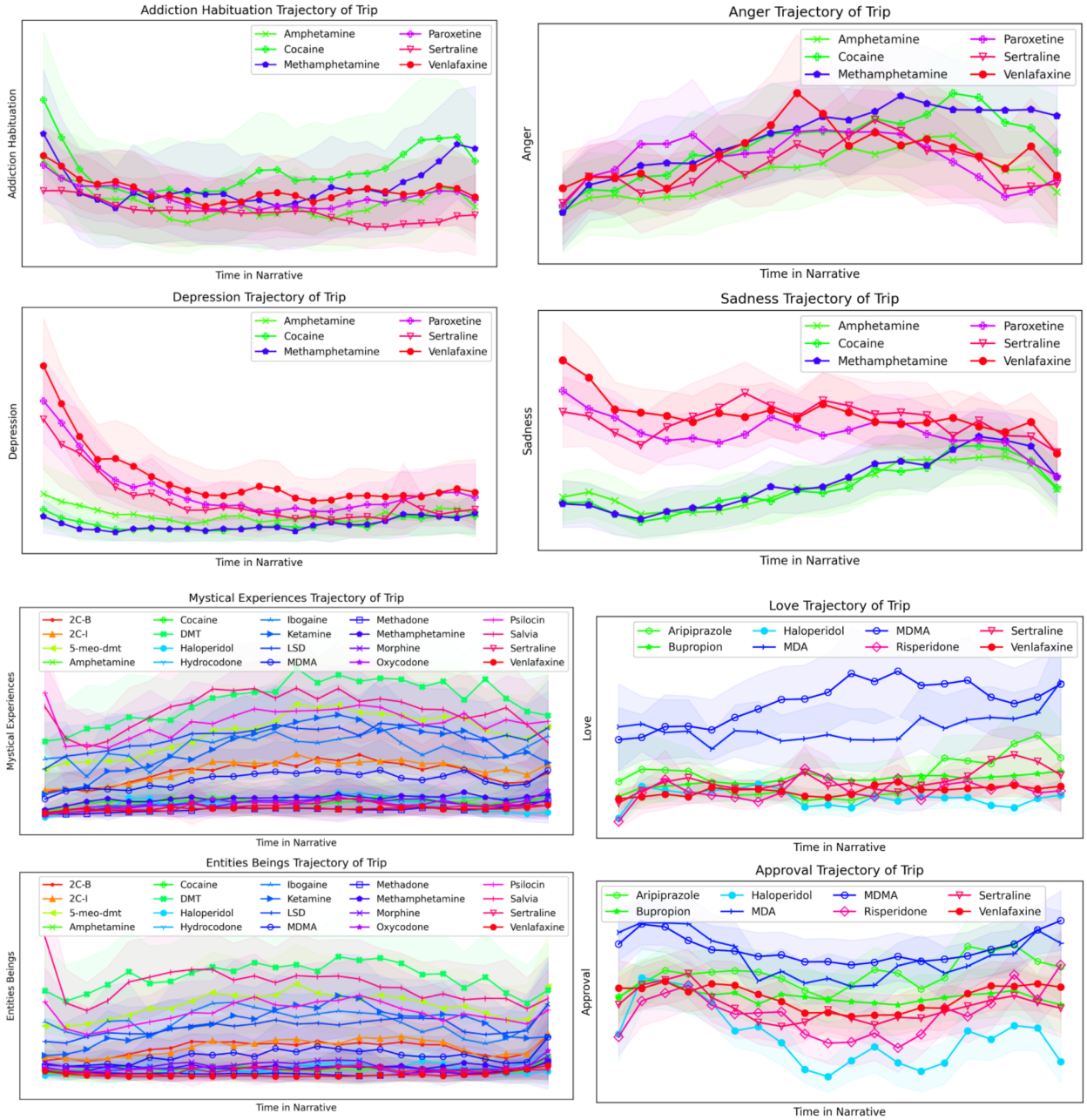
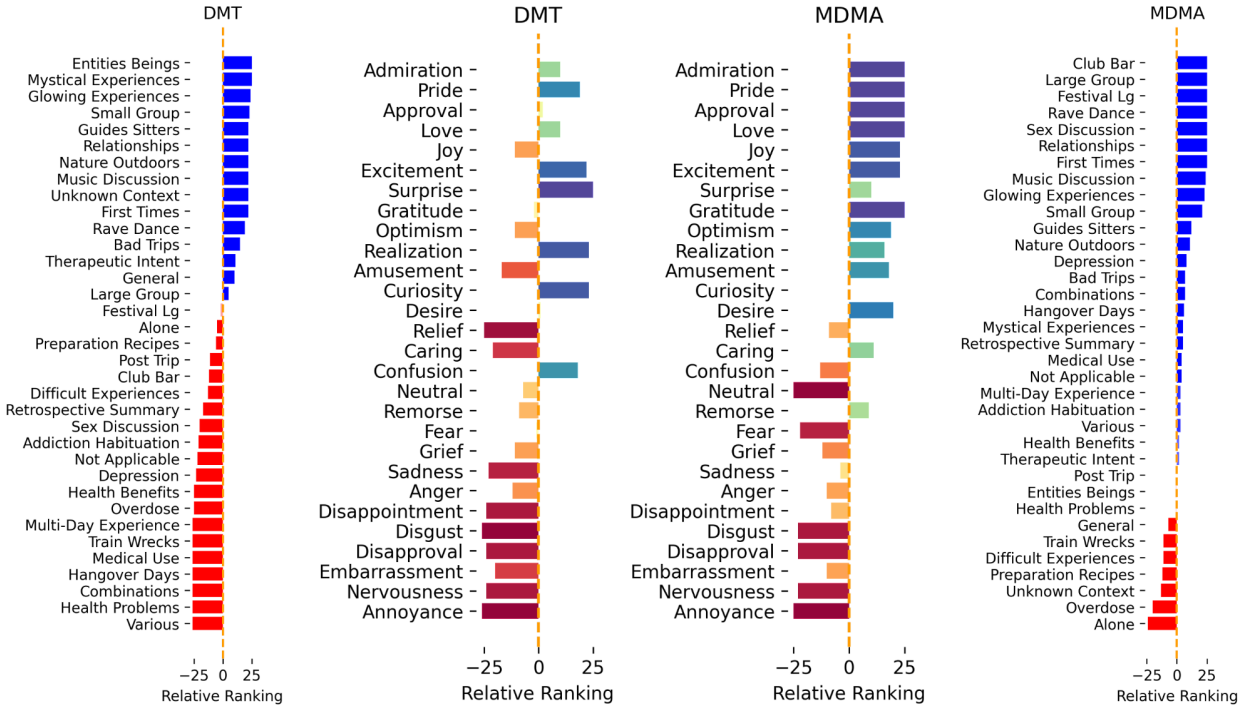
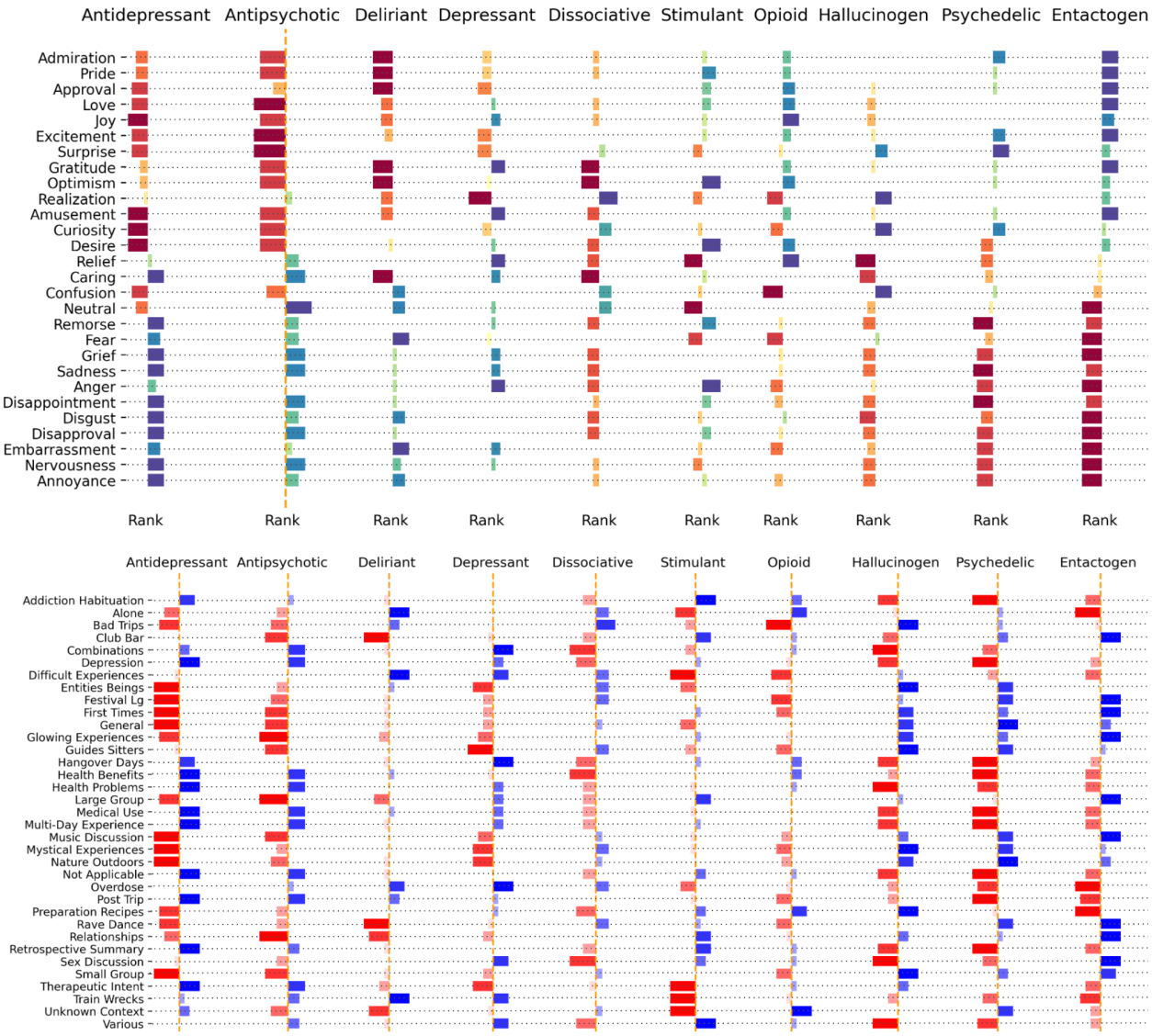


Figure: TagScapes and EmotionScapes

Panel 1: The first and last column show BERTowid's tag predictions averaged for a given drug and ranked against all other drugs. The two middle plots show the analogous ranking from the 28 output heads of BERTiment. BERTowid ranks DMT highly on "Entities/Beings" and "Mystical Experiences", while BERTiment ranks it highly "Surprise", "Realization" and "Curiosity". BERTiment's MDMA rankings shows strong correlation with the hedonic-tone ordering and BERTowid ranks MDMA least likely to be tagged "Alone". Panel 2: Averaged BERTiment predictions for the drugs belonging to each of the 10 pharmacologic classes are shown, ordered by the hedonic tone spectrum derived from IMDB. Panel 3: Averaged BERTowid tag predictions for the drugs belonging to each of the 10 pharmacologic classes are shown.





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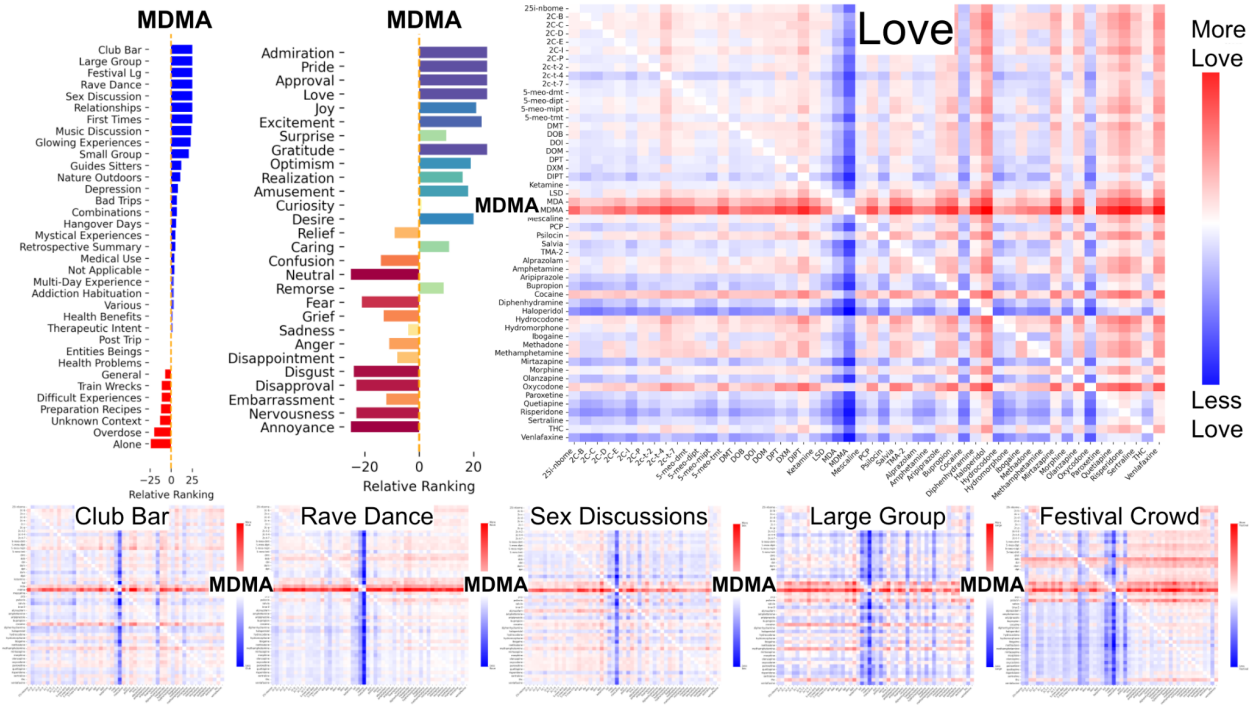
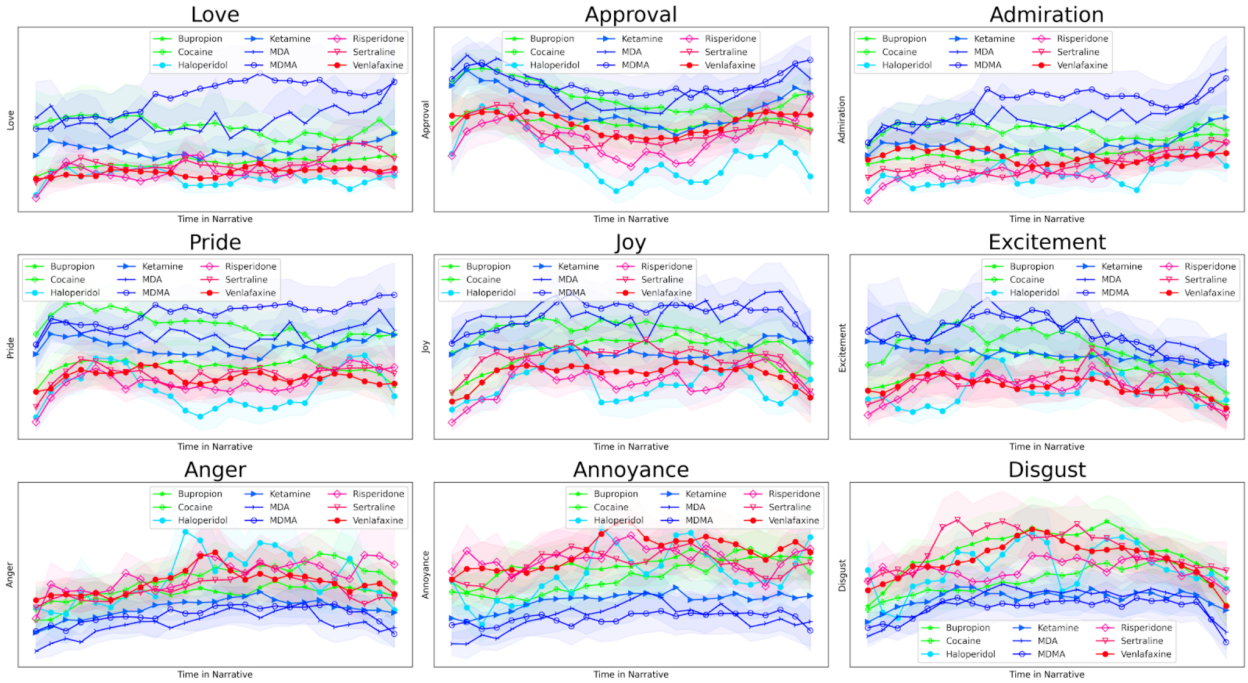
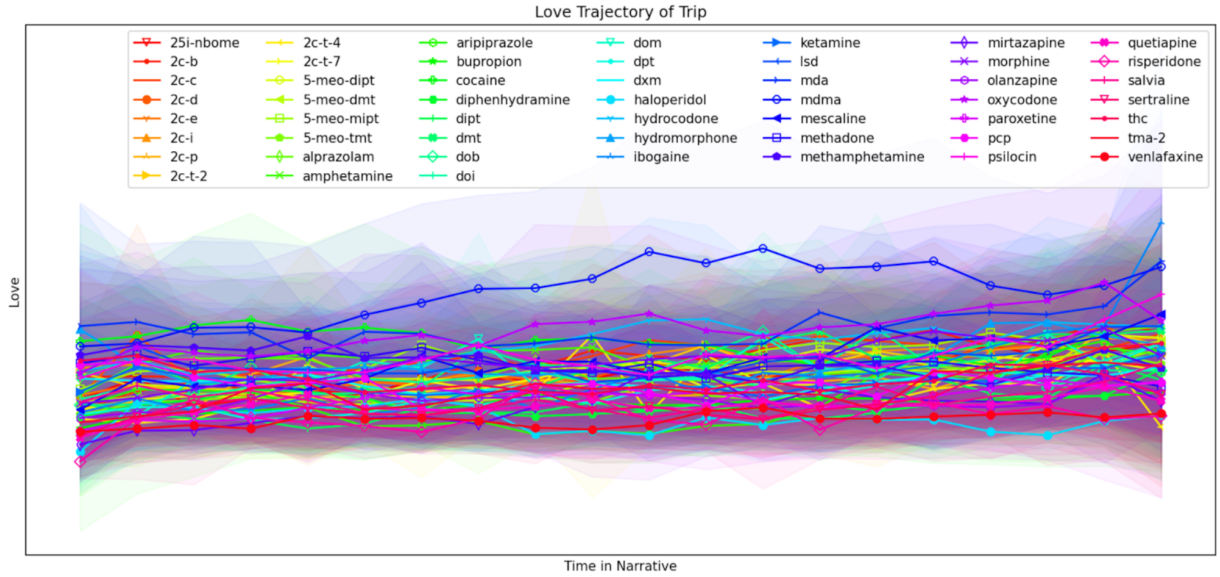
Supplementary Information

Figure: MDMA is Singular

Panel 1: The BERTowid tag predictions for MDMA compared to all other drugs, ordered from most associated (blue bars) to least associated (red bars). BERTiment sentiment averages compared all other drugs, ordered by the hedonic tone spectrum, with higher values in blue/green, lower values red/yellow. DTW for love compared against all drugs show that MDMA is the dominant love drug. Below, BERTowid tag DTW shows the universally highest ranking is for MDMA against all other drugs for tags “Club Bar”, “Rave Dance”, “Sex Discussions”, “Large Group”, and “Festival Crowd”. Panel 2: A subset of drugs representing the main pharmacologic classes are shown in terms of sentiment trajectories for “Love”, “Approval”, “Admiration”, “Pride”, “Joy”, “Excitement” (for which MDMA has high overall relative value throughout trajectory), as well as “Anger”, “Annoyance”, and “Disgust” (for which MDMA has low overall relative value through trajectory of drug experience). Lastly, the blue pole from CCA 5 reproduced below clearly highlights MDMA and related terms.




Love
Approval
Admiration
Pride
Joy
Excitement
Anger
Annoyance
Disgust
Bupropion
Cocaine
Haloperidol
Ketamine
MDA
MDMA
Risperidone
Sertraline
Venlafaxine
Time in Narrative


Love Trajectory of Trip
25i-nbome
2c-b
2c-c
2c-d
2c-e
2c-i
2c-p
2c-t-2
2c-t-4
2c-t-7
5-meo-dipt
5-meo-dmt
5-meo-mipt
5-meo-tmt
alprazolam
amphetamine
aripiprazole
bupropion
cocaine
diphenhydramine
dipt
dmt
dob
doi
dom
dpt
dxm
haloperidol
hydrocodone
hydromorphone
ibogaine
ketamine
lsd
mda
mdma
mescaline
methadone
methamphetamine
mirtazapine
morphine
olanzapine
oxycodone
paroxetine
pcp
psilocin
quetiapine
risperidone
salvia
sertraline
thc
tma-2
venlafaxine
Love
Time in Narrative

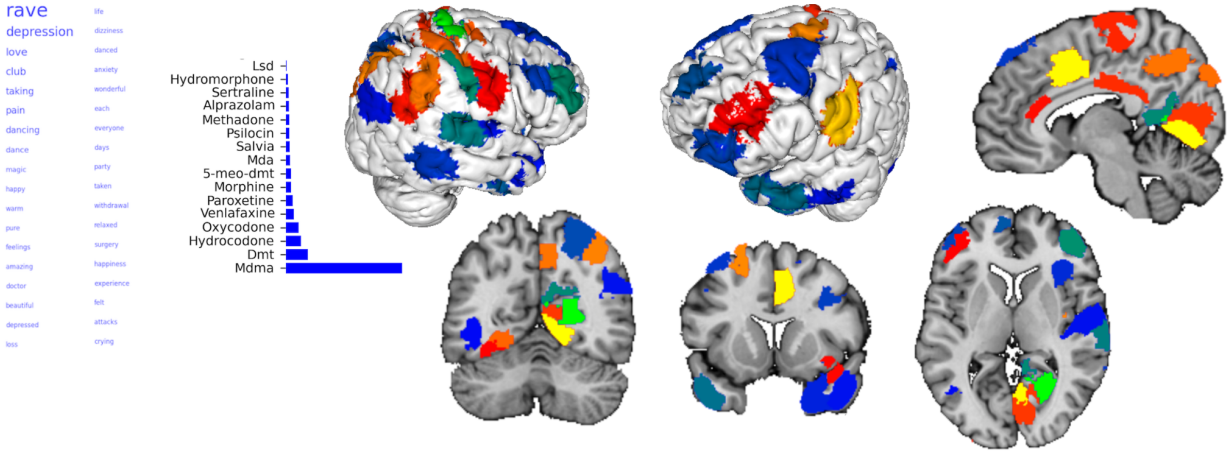
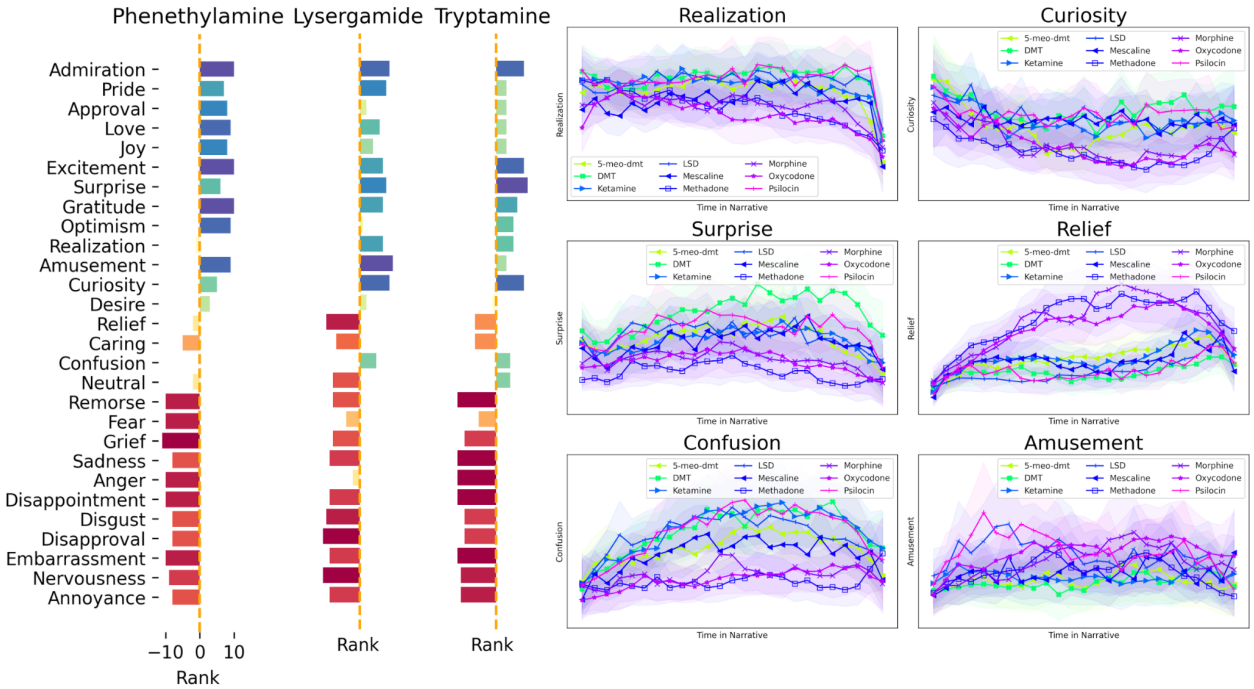
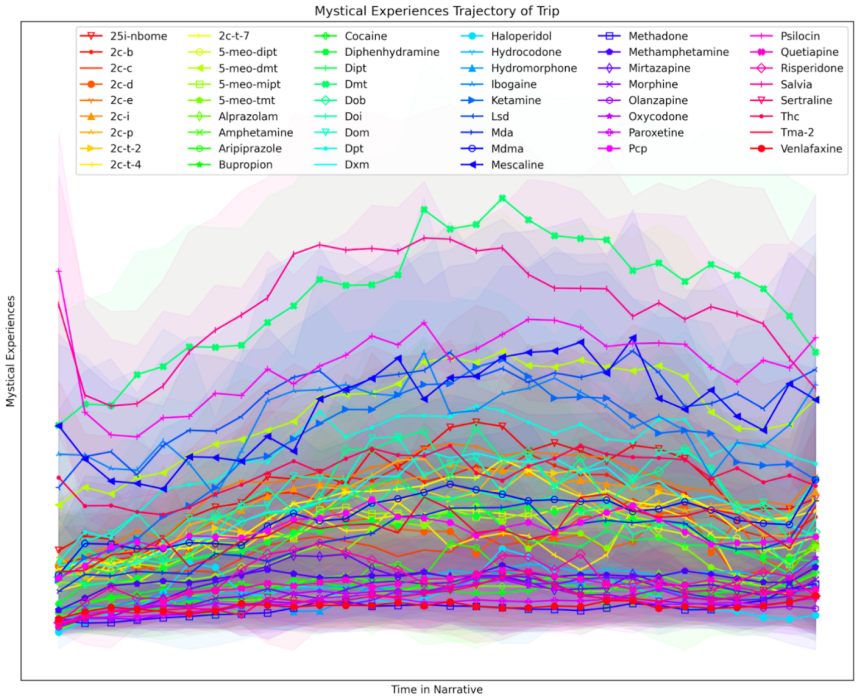

rave
depression
love
club
taking
pain
dancing
dance
magic
happy
warm
pure
feelings
amazing
doctor
beautiful
depressed
loss
life
dizziness
danced
anxiety
wonderful
each
everyone
days
party
taken
withdrawal
relaxed
surgery
happiness
experience
felt
attacks
crying
Lsd
Hydromorphone
Sertraline
Alprazolam
Methadone
Psilocin
Salvia
Mda
5-meo-dmt
Morphine
Paroxetine
Venlafaxine
Oxycodone
Hydrocodone
Dmt
Mdma

Figure: Psychedelics are Curious

Figured here are the three major psychedelic chemical classes. On the left, they are shown in terms of the averaged BERTiment sentiment values for drugs in each of these chemical classes, ordered by the hedonic tone spectrum derived from IMDB. On the right, BERTiment sentiment trajectories for a subselection of phenethylamines, lysergamide, and tryptamines, as well as, for comparison, opioids and ketamine are shown. For comparison note how, for tryptamines in particular, the weightings for surprise and curiosity are far greater than they are for MDMA.




Mystical Experiences Trajectory of Trip
25i-nbome
2c-b
2c-c
2c-d
2c-e
2c-i
2c-p
2c-t-2
2c-t-4
2c-t-7
5-meo-dipt
5-meo-dmt
5-meo-mipt
5-meo-tmt
Alprazolam
Amphetamine
Aripiprazole
Bupropion
Cocaine
Diphenhydramine
Dipt
Dmt
Dob
Doi
Dom
Dpt
Dxm
Haloperidol
Hydrocodone
Hydromorphone
Ibogaine
Ketamine
Lsd
Mda
Mdma
Mescaline
Methadone
Methamphetamine
Mirtazapine
Morphine
Olanzapine
Oxycodone
Paroxetine
Pcp
Psilocin
Quetiapine
Risperidone
Salvia
Sertraline
Thc
Tma-2
Venlafaxine
Mystical Experiences
Time in Narrative

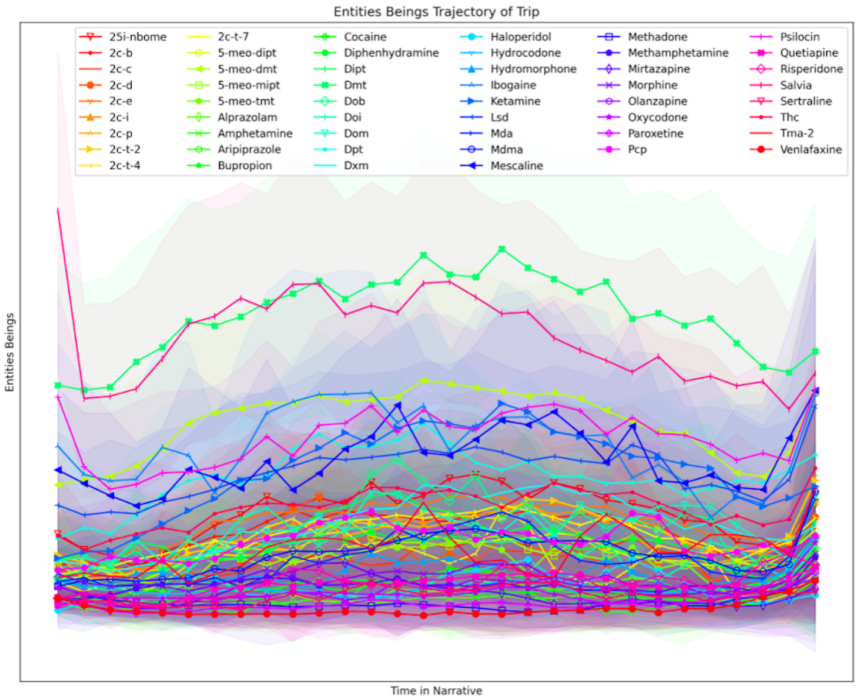

Entities Beings Trajectory of Trip
25i-nbome
2c-b
2c-c
2c-d
2c-e
2c-i
2c-p
2c-t-2
2c-t-4
2c-t-7
5-meo-dipt
5-meo-dmt
5-meo-mipt
5-meo-tmt
Alprazolam
Amphetamine
Aripiprazole
Bupropion
Cocaine
Diphenhydramine
Dipt
Dmt
Dob
Doi
Dom
Dpt
Dxm
Haloperidol
Hydrocodone
Hydromorphone
Ibogaine
Ketamine
Lsd
Mda
Mdma
Mescaline
Methadone
Methamphetamine
Mirtazapine
Morphine
Olanzapine
Oxycodone
Paroxetine
Pcp
Psilocin
Quetiapine
Risperidone
Salvia
Sertraline
Thc
Tma-2
Venlafaxine
Entities Beings
Time in Narrative

Figure: Dynamic Time Warp Distance Between 17 Emotions Supports CCA 0

CCA 0, the dominant component from CCA, grouped the 52 drugs similarly to many of the emotion Dynamic Time Warp matrices from BERTiment. Note how all 12 of the DTW matrices in the top half of the figure have bluish upper diagonals and reddish lower diagonals and the opposite pattern for the 5 emotions in the lower half of the image.

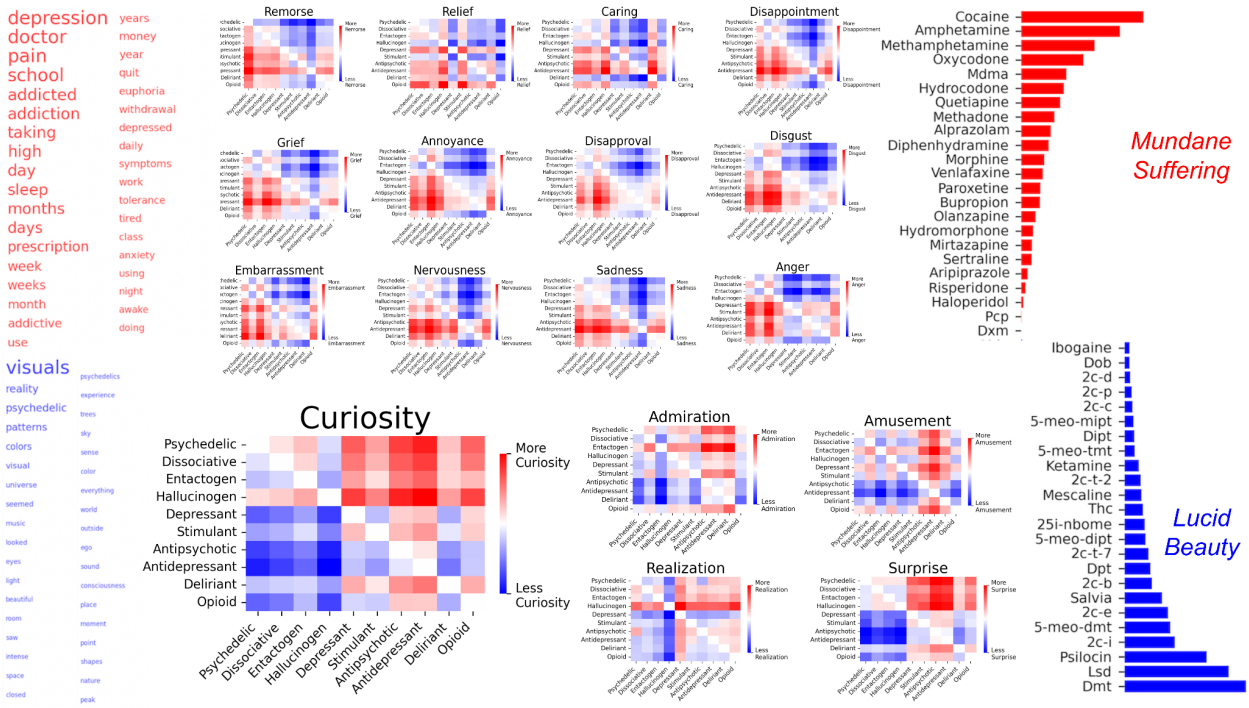
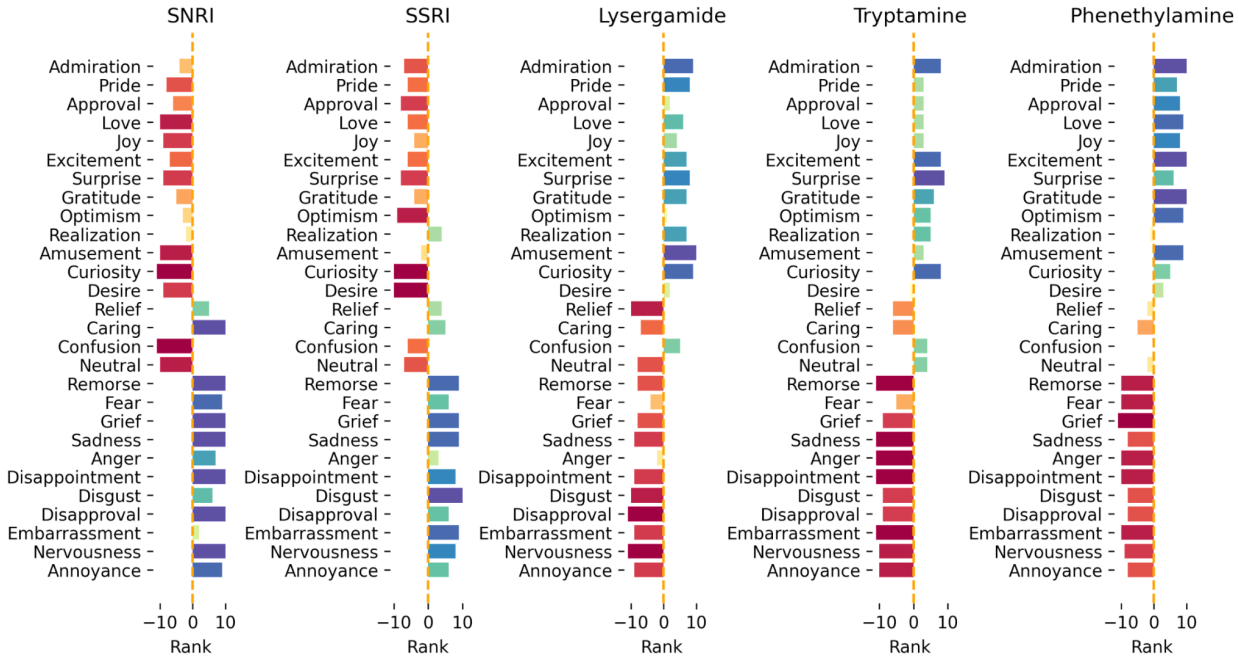


Figure: Emotion-Scapes

This figure represents averaged BERTiment sentiment predictions organized first by drug chemical class and then by individual drugs. Panel 1: For a selection of drug chemical classes, BERTiment's 28 output heads for sentiment, with predictions averaged and ranked against all other drugs. One prominent pattern that is brought into relief by these histograms is that tryptamines, phenethylamines, and lysergamides are tilted towards positive hedonic tone while SNRIs and SSRIs show the inverse pattern of sentiment rankings. Panel 2: Analogous averaged BERTiment sentiment values for a subset of key drugs are shown here.



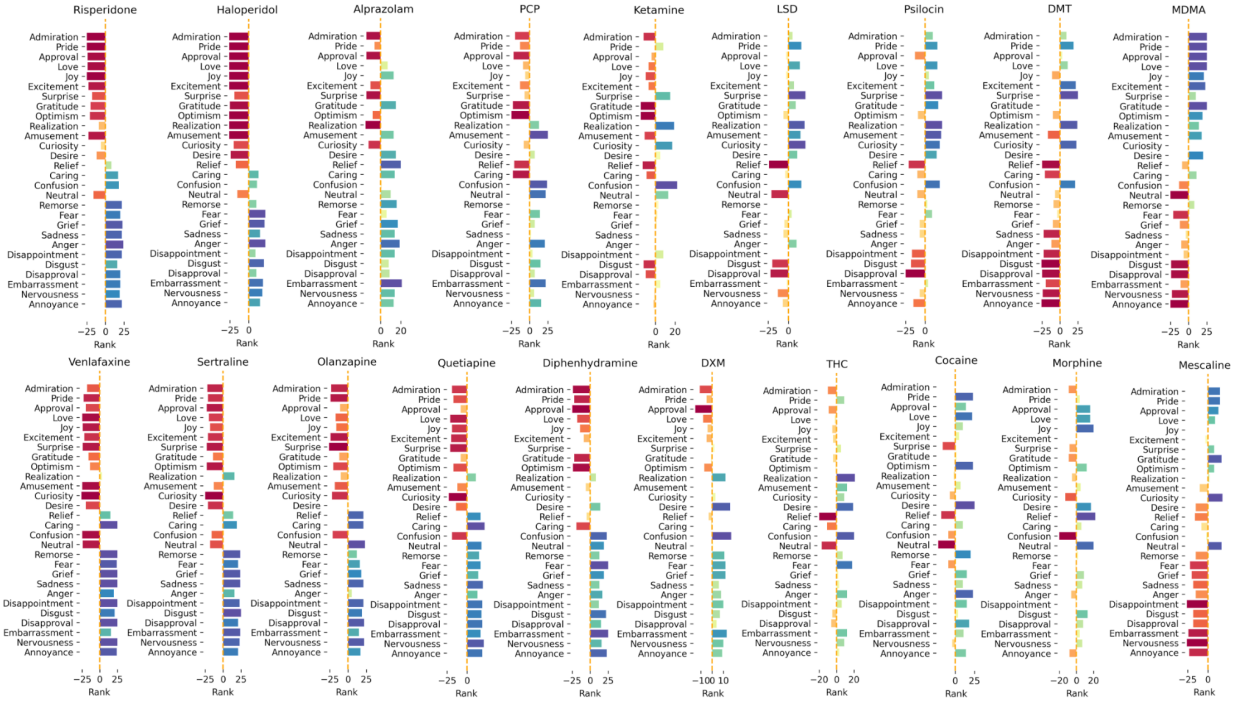

Risperidone
Haloperidol
Alprazolam
PCP
Ketamine
LSD
Psilocin
DMT
MDMA
Venlafaxine
Sertraline
Olanzapine
Quetiapine
Diphenhydramine
DXM
THC
Cocaine
Morphine
Mescaline
Admiration
Pride
Approval
Love
Joy
Excitement
Surprise
Gratitude
Optimism
Realization
Amusement
Curiosity
Desire
Relief
Caring
Confusion
Neutral
Remorse
Fear
Grief
Sadness
Anger
Disappointment
Disgust
Disapproval
Embarrassment
Nervousness
Annoyance
Rank

Figure: Tag-Scapes

This figure represents averaged BERTowid tag predictions for a selection of key drugs. BERTowid predictions are averaged and ranked against all other drugs. They are ordered in a customized manner for each drug, with higher ranking for tags represented by blue bars and lower ranking shown by red bars.

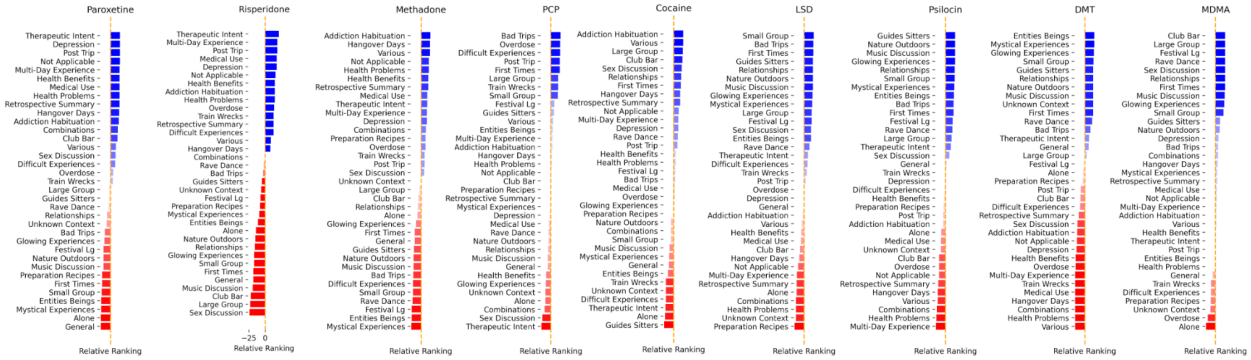


Figure: Compare Trajectories with Dynamic Time Warps

BERTiment sentiment trajectory for “Love” is shown for all drugs, as an average of all testimonials for each individual drug. Visible to the plain eye, with MDMA has the highest value through the majority of the duration of drug experience. The chart on the upper right confirms this through dynamic time warping with MDMA creating a bright red line of “Love” slicing across the center from the y-axis. DTW by pharmacologic class shows entactogens (MDMA & MDA), compared to all other pharmacologic classes, have relatively low values for “Grief”, high values for “Joy” and “Love”, and moderate values for “Curiosity”.

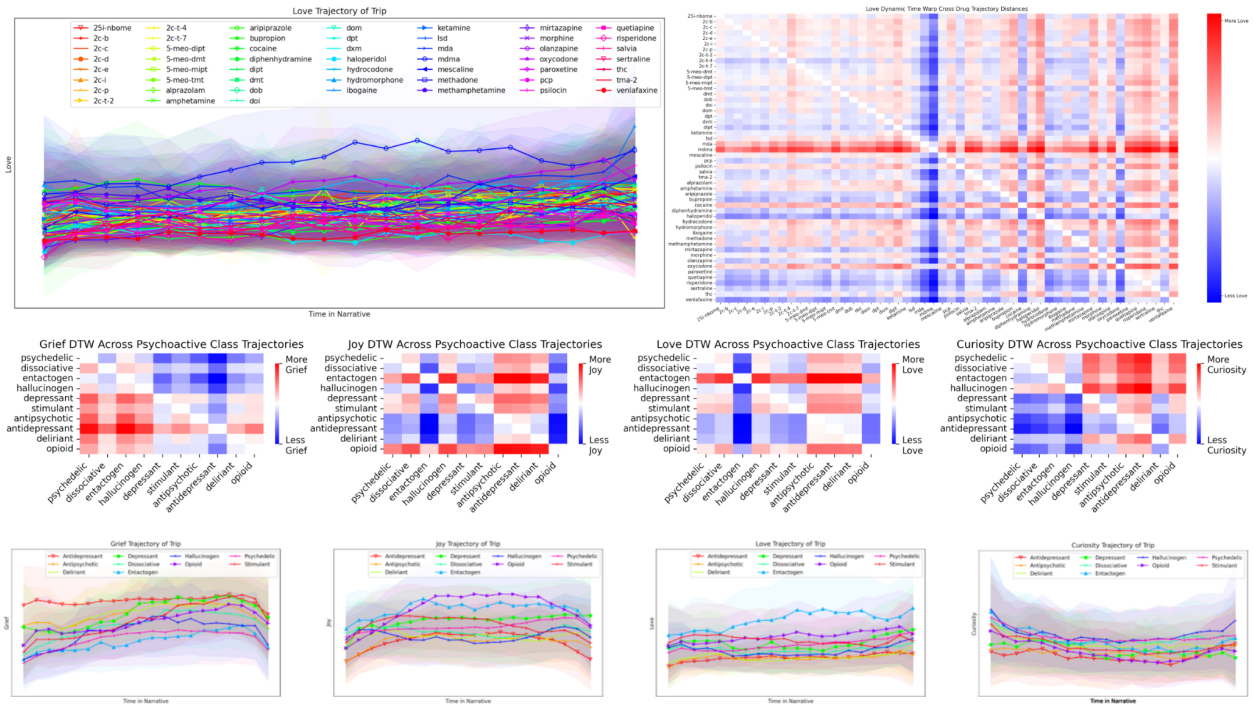


Figure: Optimism and Neutral Trajectories

While many sentiment trajectories showed substantial differences between drugs and drug classes, trajectories from the sentiments “Neutral” and “Optimism” were remarkably uniform across all drug groupings. “Neutral” gradually decreases over the course of the narrative. In contrast, “Optimism” showed an early, uniform rise then stayed steady for the most of the drug experience before uniformly increasing at the end.

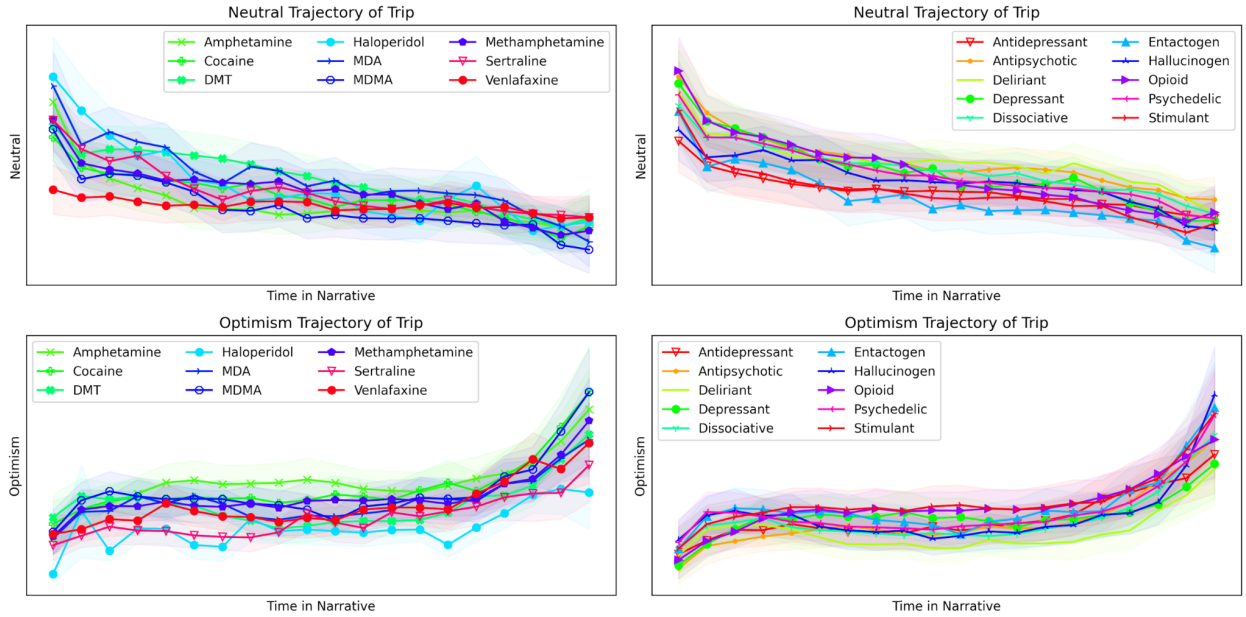


Figure: CCA 0

The dominant component across all drug experiences highlights a tension between terms relating to *lucid-beauty* and *mundane-suffering.* The most statistically significant CCA component linking receptor binding affinity to word usage across [x] words in11,821 testimonials of real-world experiences induced by 52 compounds is shown here. **Left**: A weighted list of words comprising the semantic theme of each extreme (red and blue) of this receptor-experience vector. Bigger words represent relatively larger ranking in this component. **Right**: Receptor affinity values most closely associated with this receptor-experience component are sorted by their relative ranking; blue bars correspond to blue words on the left while red bars correspond to red words. **Middle**: The middle panel shows how strongly each drug correlated to this receptor-experience component. Again, blue bars correspond to the blue words and receptors, while red bars correspond to the red words and receptors. **Main**: Brain renderings and surfaces highlight which of the 200 parcellated anatomical regions were found to most densely express the receptor-gene RNA as described by Allen's Human Brain Atlas. Sagittal left, sagittal right, and axial brain slices are shown at x = -7, x = +8, and z = +8 of MNI-space, respectively. The colors of each rendering represent the density of weighted receptor gene expression for each region and correspond to the extremes of this component: blue words and bars correspond to blue/greed brain regions (green > blue intensity), while red words and bars correspond to the red/yellow brain regions (yellow > red intensity). The surfaces show the weighted receptor expression on the surface of the cortex using Mango.

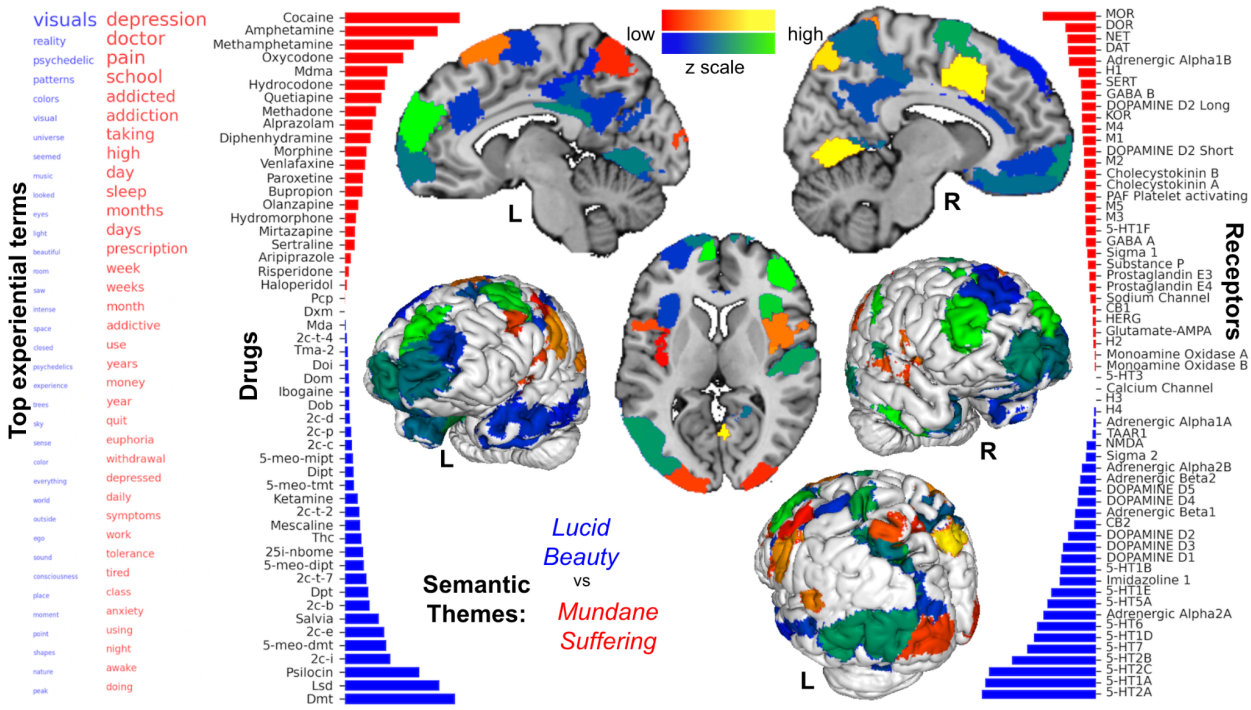


Figure: CCA 1

The second significant component underlying drug experience charts a dichotomy between *depression-insomnia* and *impulsivity-addiction.* This component captured a motif of impulsivity (*rush, party, craving)* and addiction (*dealer, addicted, hooked, bought*), see Figure: CCA 1. These terms were associated with the drugs cocaine, methamphetamine, and MDMA, as well as receptor affinity at CB1, DAT, CB2 and with expression of these receptor genes in the primary visual and sensory cortices. The opposite extreme flagged terms relating broadly to mental illness (*anxiety, depression, symptoms, diagnosed, psychotic, bipolar*) and treatment (*doctor, psychiatrist, medicine, treatment)*. This semantic theme was associated most with the drugs quetiapine, diphenhydramine, and DXM, as well as receptor affinity to H1, 5-HT2A, and D2 receptors. The expression of these receptor genes was found to be most dense across the distribution of the default mode network including the posterior cingulate cortex, ventromedial prefrontal cortex, and the inferior parietal lobules. Sagittal and axial brain slices are shown at x = 5 and z = -11.

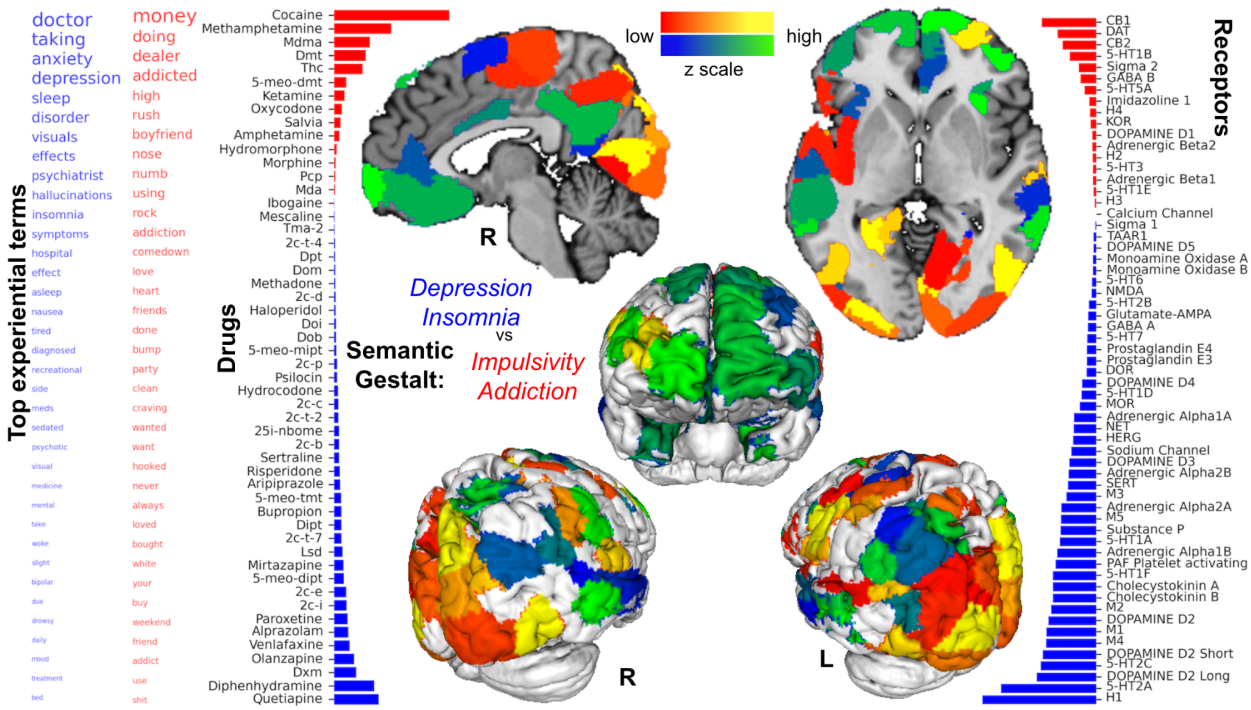


Figure: CCA 2

The third significant receptor-experience component tracked two extremes: *perception-celebration* and *cosmic-expansion*. This component identified, at one extreme, a collection of terms denoting cosmic (*universe, space, dimension, breakthrough*), awareness (*remember, dream, consciousness*) qualities of subjective experience, and entities (*beings, spirit, entity, alien*) that were nested in a temporal horizon of immediacy (*seconds*). This

conceptual cluster was associated with drugs THC, DMT, Salvia, Ketamine, and 5-MeO-DMT, as well as receptor affinity at CB1, CB2, KOR, M1, and 5-HT7, and the expression of these receptor genes was most dense in the medial prefrontal cortex, dorsal anterior cingulate cortex, and temporoparietal junction. The opposite extreme of this component was characterized by terms relating to perception (*visuals, music, tracers*), somatic sensation (*nausea, effects, stomach, ingested, sex*), and intensity (*peak, comedown, amazing, mild*) situated in a time-horizon of *hours.* This aggregation of terms was associated with drugs MDMA, 2C-I, and 2C-E, as well as receptor affinities at 5-HT2A, Alpha 2A, and 5-HT2C, and the expression of these receptor genes was most dense in the primary visual cortex as well as areas of the primary sensory and motor cortices. Sagittal and axial brain renderings are shown at x = -6 and z = 8.

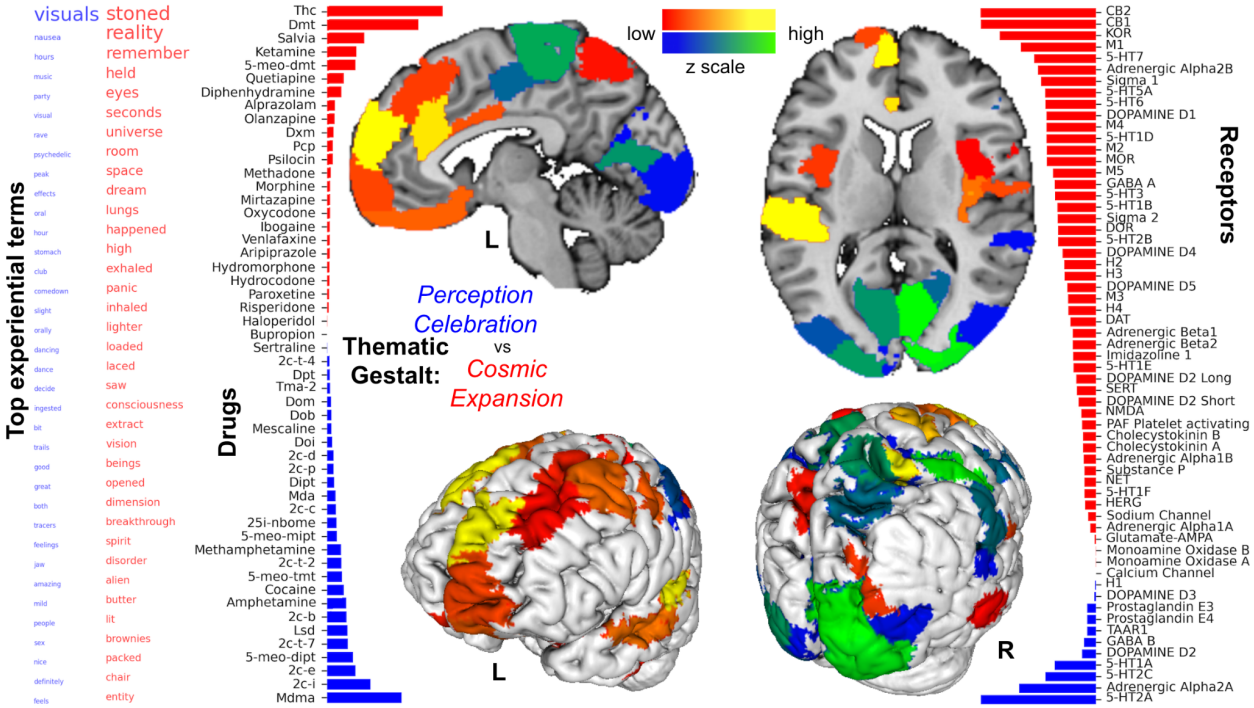


Figure: CCA 3

Receptor-experience component CCA 3 highlighted *bad-high* and *pain-relief.* This component tied together a range of terms relating to psychopathology including (*depression, anxiety, panic, paranoid, insomnia, psychotic*), diagnosis (*psychiatrist, disorder, diagnosed, symptoms*), and substance use (*stoned, rave, party, club, laced*). This theme of substance-related psychopathology was associated with drugs THC, MDMA, LSD, methamphetamine, and amphetamine. Receptor affinity weightings favored 5-HT2B, Alpha 2A, and Alpha 1A, while gene receptor expression was most dense in the medial prefrontal cortex, anterior insula, and dorsal anterior cingulate cortex. The opposite pole of this vector charted a subjective theme of discomfort (*pain, nausea, itching, sick)* and comfort (*warm, relaxed, euphoria, nice)*. This semantic spectrum of comfort was associated with drugs oxycodone, hydrocodone, DMT, methadone, and ketamine, receptor affinity for MOR, KOR, and DOR receptors, and receptor

gene expression in the primary visual cortex, precuneus, and mid-cingulate cortex.Sagittal left, sagittal right, and axial brain renderings are shown at x = -6, x = +8, and z = -9, respectively.

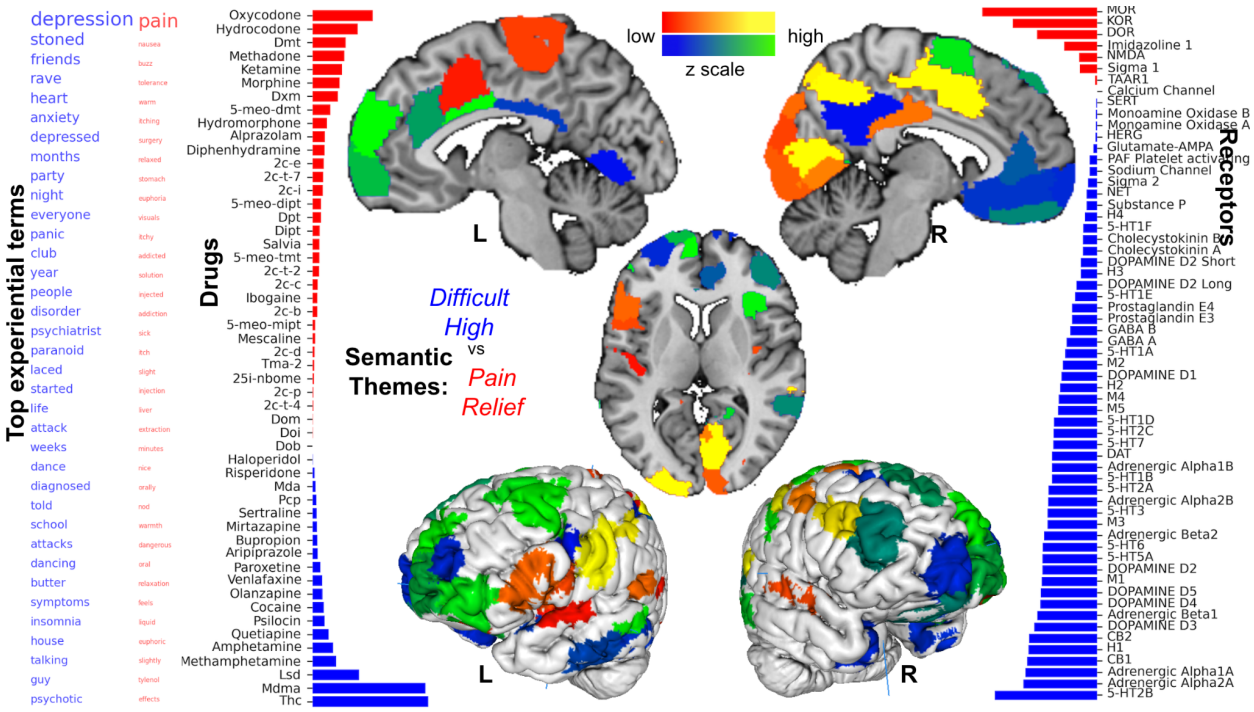


Figure: CCA 4

The fifth receptor-experience component uncovered *edibles* and *bipolar* phenomena. This component identified by CCA captured a semantic theme rich with terms relating to both the manic *(energy, insomnia, rush, intensity, psychotic, money*) and the depressive *(depression, mood, insomnia, anxiety)* phases of bipolar illness. This theme was associated with drugs DMT, cocaine, 5-MeO-DMT, and methamphetamine, as well as receptor affinity at 5HT1A, 5HT7, 5HT2C, and 5HT1D, and the expression of these receptor genes was densest across the distribution of the default mode work (medial prefrontal cortex, posterior cingulate cortex, medial temporal lobes) and salience network (dorsal anterior cingulate cortex, anterior insula). The converse semantic extreme of this component clustered words relating to inebriation (*stoned, high, laughing*), somatic discomfort (*cough, pain, itching, sick*), and oral consumption (*laced, brownies, food, butter, bowls, bottles, drank*). This linguistic gestalt was linked to drugs THC, DXM, and diphenhydramine, receptor affinity at CB1, CB2, and MOR, and receptor gene expression especially in the visual cortex. Sagittal left, sagittal right brain renderings are shown at x = -6 and x = +8, respectively.

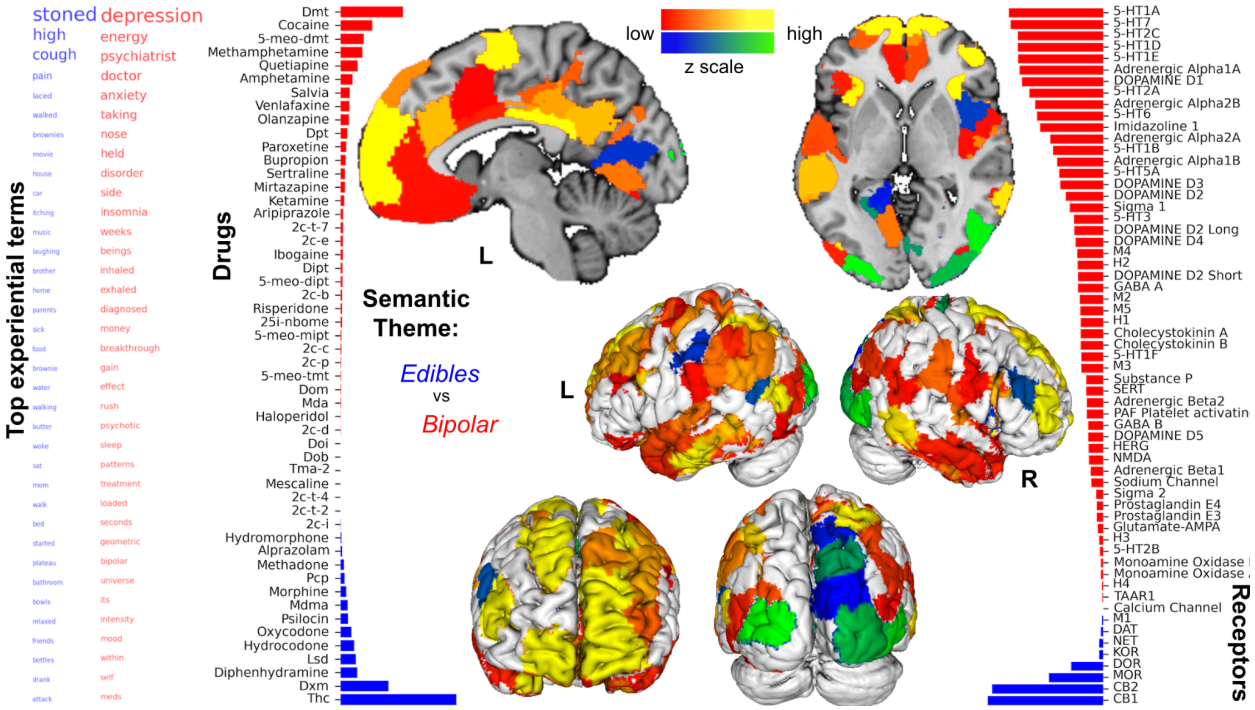


Figure: CCA 5

The sixth receptor experience component revealed *emotional-extremes* and *drug-induced-psychosis.* This component identified a constellation of terms describing a rich array of emotions, ranging from positive (*love, happy, warm, pure, amazing, beautiful, wonderful, relaxed*) to negative (*depression, loss, anxiety, crying*), as well as a context of a nightclub or “rave” (*rave, club, dancing, party*). This semantic pattern was strongly linked to drug MDMA, with receptor affinity at 5HT2B and Alpha 2B, and receptor gene expression isolated to the primary visual cortex and primary sensory regions innervating the trunk, head, and neck. The opposite extreme of this component flagged a pattern of terms tying together psychosis (*visuals, hallucinations, auditory, voices, hospital, psychotic, psychosis*) and addiction (*money, bump, dealer, addiction, addicted, addict*). This semantic theme was associated with receptor affinity at H1, 5-HT2A, and CB2, as well as receptor gene expression in the mid-cingulate and visual cortices. Sagittal left, axial, coronal posterior, and coronal anterior rendered brain slices are shown at x = +8, z = +4, y = -57, and y = +6, respectively.

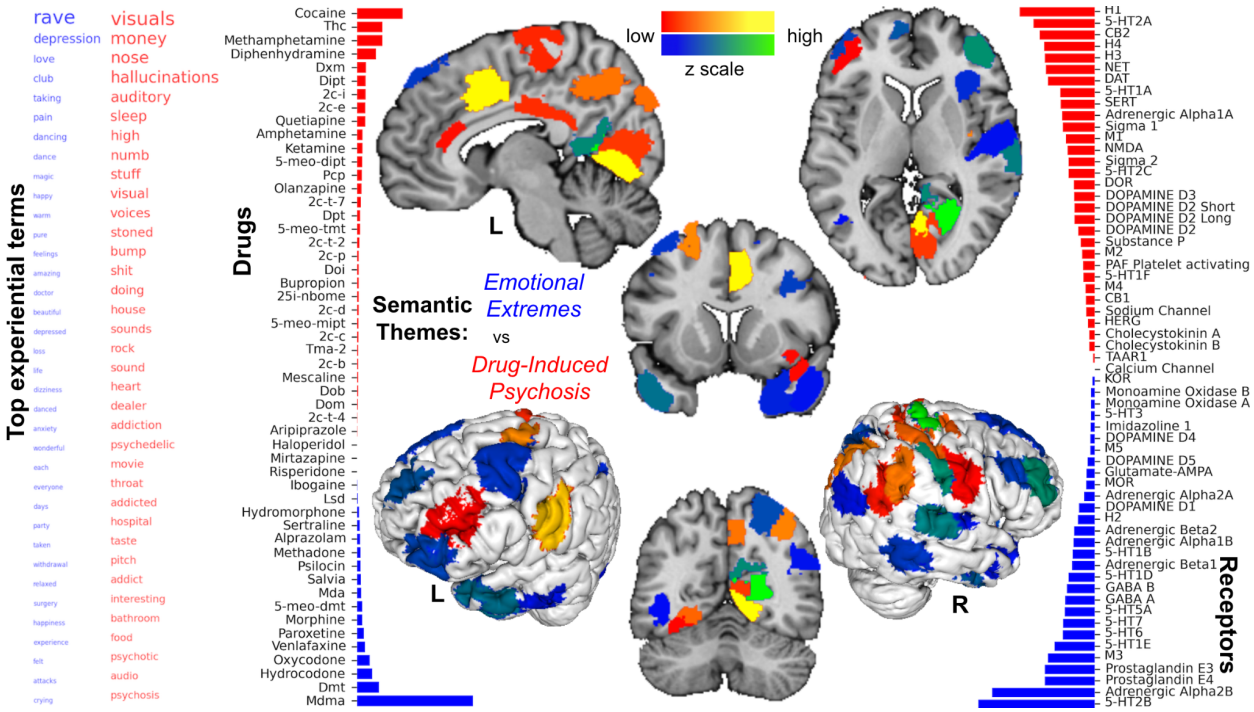


Figure: CCA 6

Receptor experience component CCA 6 revealed *emotional-extremes* and *drug-induced-psychosis.* This component distilled a semantic cluster of terms relating to somatic sensation (*pain, nausea, ate, warm, heart, relaxed*) and intoxication (*stoned, high, laced, strong, brownies*). This constellation of terms was mostly linked to THC, as well as receptor affinity at 5-HT2A, CB2, and CB1, and receptor gene expression isolated to the primary sensory cortex corresponding to the dermatomes of the head, neck, and torso. The opposite extreme of this component flagged words relating to liminal states (*plateau, remember, drunk, hallucinations, woke, spiders, night, memory, hole*). This semantic theme was associated with drugs DXM, MDMA, diphenhydramine, and ketamine, as well as receptor affinity at SERT, NET, and M3 receptors with gene expression for these receptor subtypes isolated primarily to the mid-cingulate cortex. Sagittal left, sagittal right brain renderings are shown at x = -6 and x = +8, respectively.

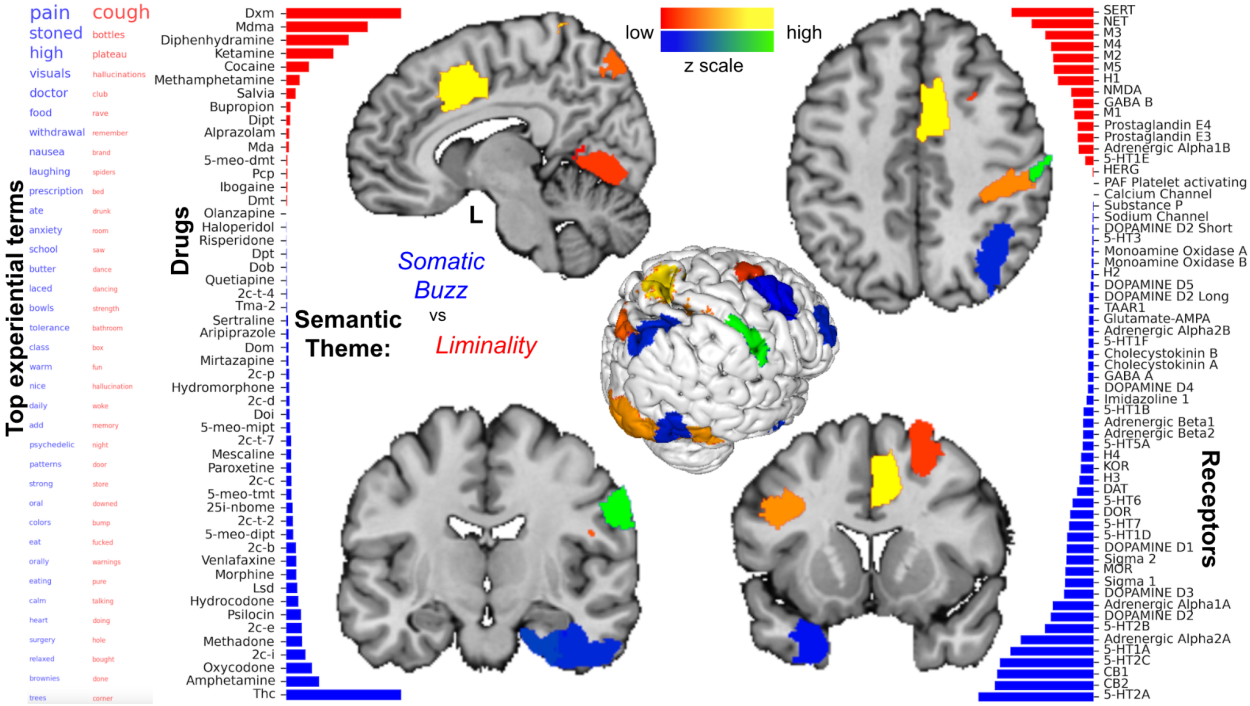


Figure: CCA 7

Receptor-experience component CCA 7 highlighted *attention* and *auditory-distress.* This component also identified terms describing audition (*auditory, sound, pitch, voices, audio*) and distress (*depression, withdrawal, anxiety, suffered, suicidal, panic*). These terms were associated with drugs amphetamine, DiPT, venlafaxine, paroxetine, as well as receptor affinity at SERT, NET, CB2, Sigma 2, and expression of these receptor genes in the salience network (dorsal anterior cingulate cortex and anterior insula) and medial prefrontal cortex. The opposing extreme linked a set of terms relating to psychosis (*psychotic, psychosis, visuals, hospital*) as well as various levels of arousal and hedonic tone (*sedated, lethargic, tired, pleasant, amazing, beautiful, wonderful*). This semantic pattern was associated with drugs quetiapine, MDMA, LSD, and olanzapine, as well as receptor affinity at 5-HT2A, 5-HT2C, D3, and D2 receptors, and receptor gene expression in the visual and mid-cingulate cortices. Sagittal, axial ventral, axial dorsal, and coronal brain slice renderings are shown at x = -5x, z = -8, z = +18, and y = -6, respectively.

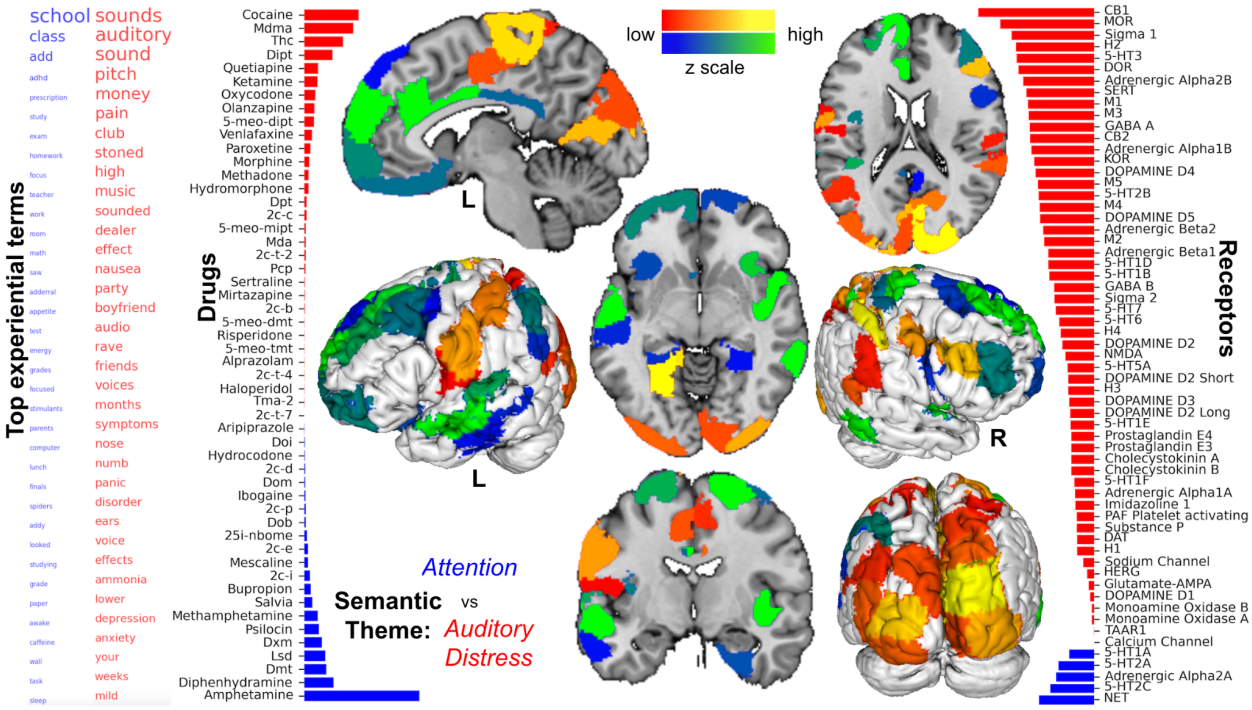


Figure: CCA 8

This component identified a similar set of terms describing audition (*auditory, sound, pitch, voices, audio*) and distress (*depression, withdrawal, anxiety, suffered, suicidal, panic*). These terms were associated with drugs amphetamine, DiPT, venlafaxine, paroxetine, as well as receptor affinity at SERT, NET, CB2, Sigma 2, and expression of these receptor genes in the salience network (dorsal anterior cingulate cortex and anterior insula) and medial prefrontal cortex. The opposing extreme linked a set of terms relating to psychosis (*psychotic, psychosis, visuals, hospital*) as well as various levels of arousal and hedonic tone (*sedated, lethargic, tired, pleasant, amazing, beautiful, wonderful*). This semantic pattern was associated with drugs quetiapine, MDMA, LSD, and olanzapine, as well as receptor affinity at 5-HT2A, 5-HT2C, D3, and D2 receptors, and receptor gene expression in the visual and mid-cingulate cortices. Sagittal, axial ventral, axial dorsal, and coronal brain slice renderings are shown at x = -5x, z = -8, z = +18, and y = -6, respectively.

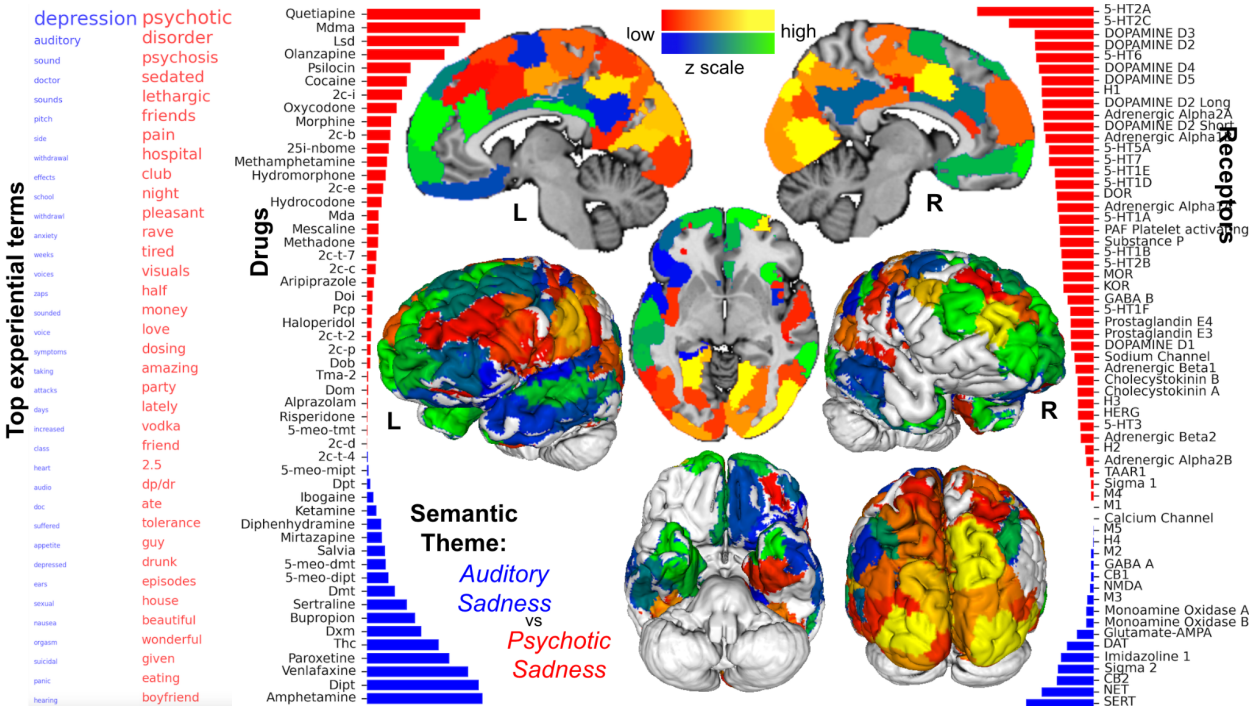


Figure: CCA 9

Receptor-experience component CCA 9, shows *sexual-angst* and *auditory-inensity.* This component highlighted a semantic theme angst (*depression, anxiety, attacks, panic, suicidal, depressive, sick*) and sexuality (*sexual, orgasm, sex*). This semantic pattern was associated with drugs DXM, cocaine, venlafaxine, and paroxetine, as well as receptor affinity at SERT, 5-HT2A, and 5-HT2C, and gene expression of these receptors in the visual and primary sensory cortices. The opposite extreme of this component tracked a set of terms relating to sound (*auditory, sound, voices, pitch, audio, music, ringing*) and arousal (*rave, love, buzz, crash, dance*). This semantic gestalt was associated with drugs amphetamine, MDMA, DiPT, and DMT, as well as receptor affinity at 5-HT2B, Alpha 2B, imidazoline 1, and CB1. Expression of these receptor genes was most dense in the primary and secondary auditory cortices, anterior insula, dorsal anterior cingulate cortex, and medial prefrontal cortex. Sagittal left, sagittal right, axial, and coronal brain slice renderings are shown at x = -6, x = +41, z = -3, and y = +25, respectively.

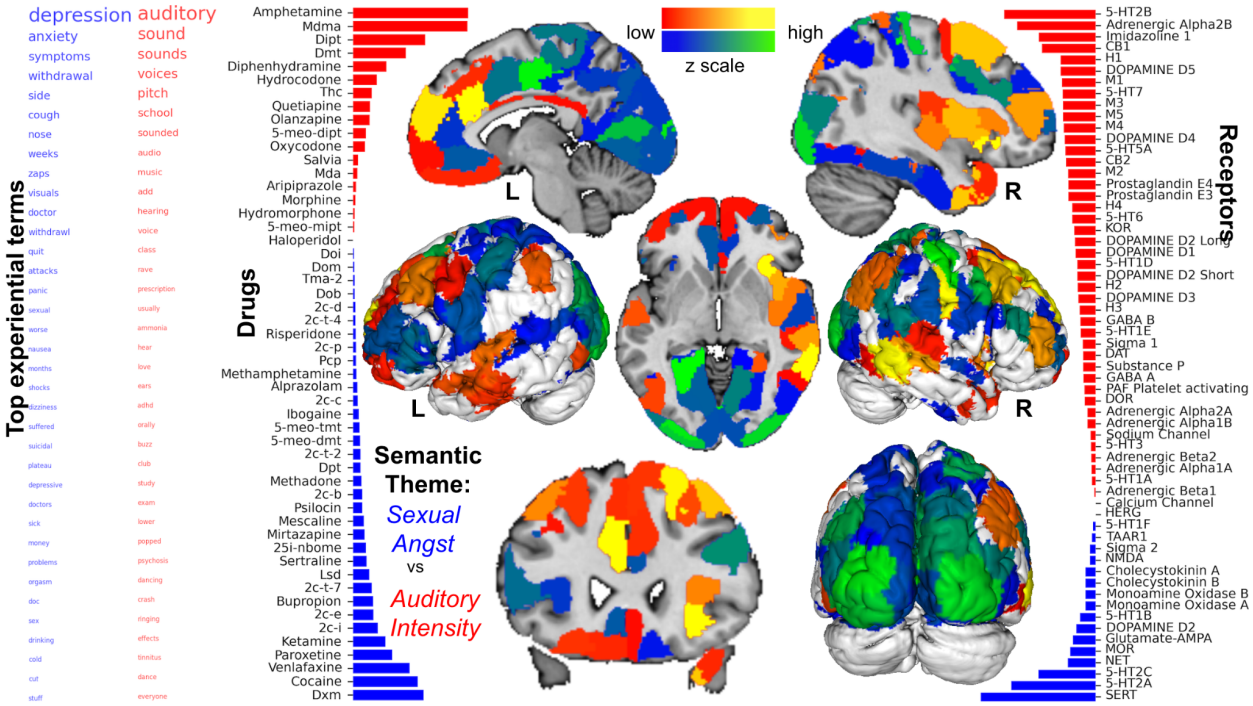


Figure: CCA 10

Receptor-experience component CCA 10 shows *sexual-angst* and *auditory-inensity.*
This component tracked a semantic constellation of terms relating to retching (cough, pukes, nausea, stomach, vomit) and ailment (itching, sick, doctor, diagnosed, psychiatrist, pain, warnings, meds, disorder). This phenomenal pattern was most associated with drug DXM and amphetamine, as well as receptor affinity at SERT, MOR, KOR, and DOR, and with expression of these receptor genes in the primary visual cortex, mid-cingulate cortex, and bilateral posterior insula. The opposite extreme of this component identified a set of words evoking eerieness (spiders, hallucinations, weird, freaked, anxiety) and physical environment (mom, car, door, wall, room, home, driving, corner, fell). This final semantic pattern was associated with drug diphenhydramine, LSD, and alprazolam, as well as receptor affinity at H1, 5-HT2A, and 5-HT2C, and with expression of receptor genes in the precuneus and primary sensory cortices.
Sagittal, and coronal brain slice renderings are shown at x = +7, z = 0, and y = +1, respectively.

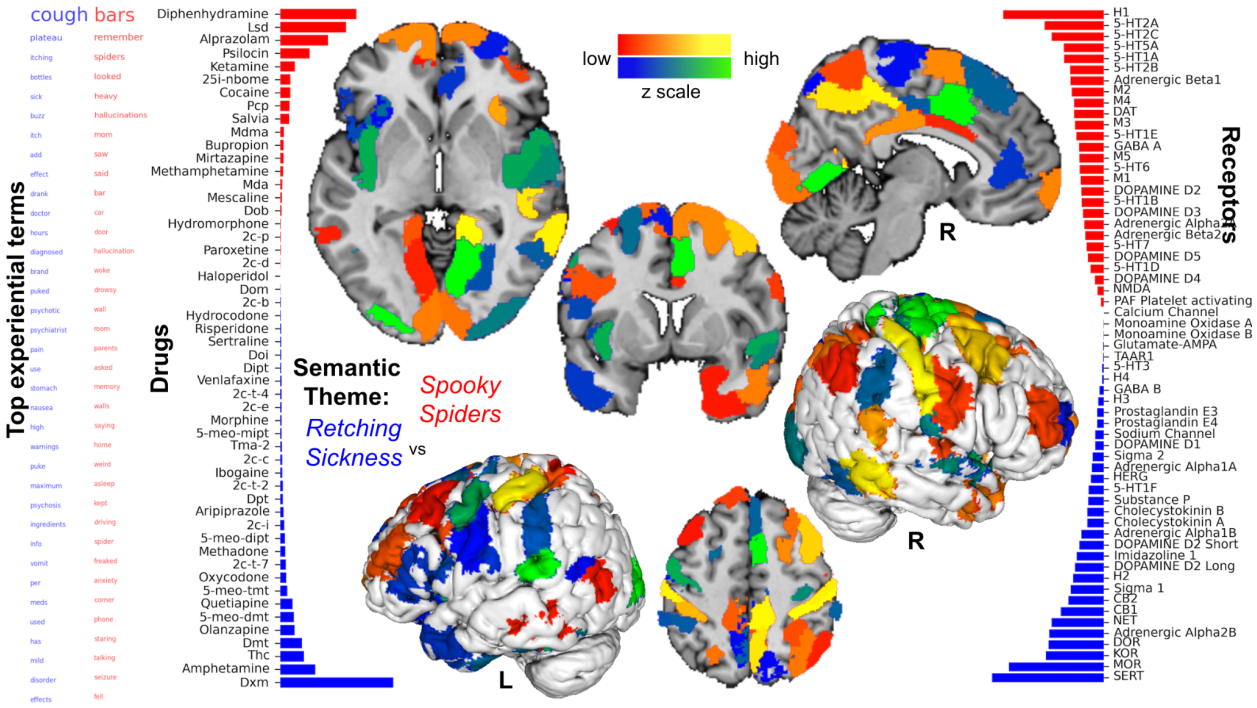


Figure: Data

High-level overview of the data sources aggregated to train BERTowid, BERTiment, and CCA.

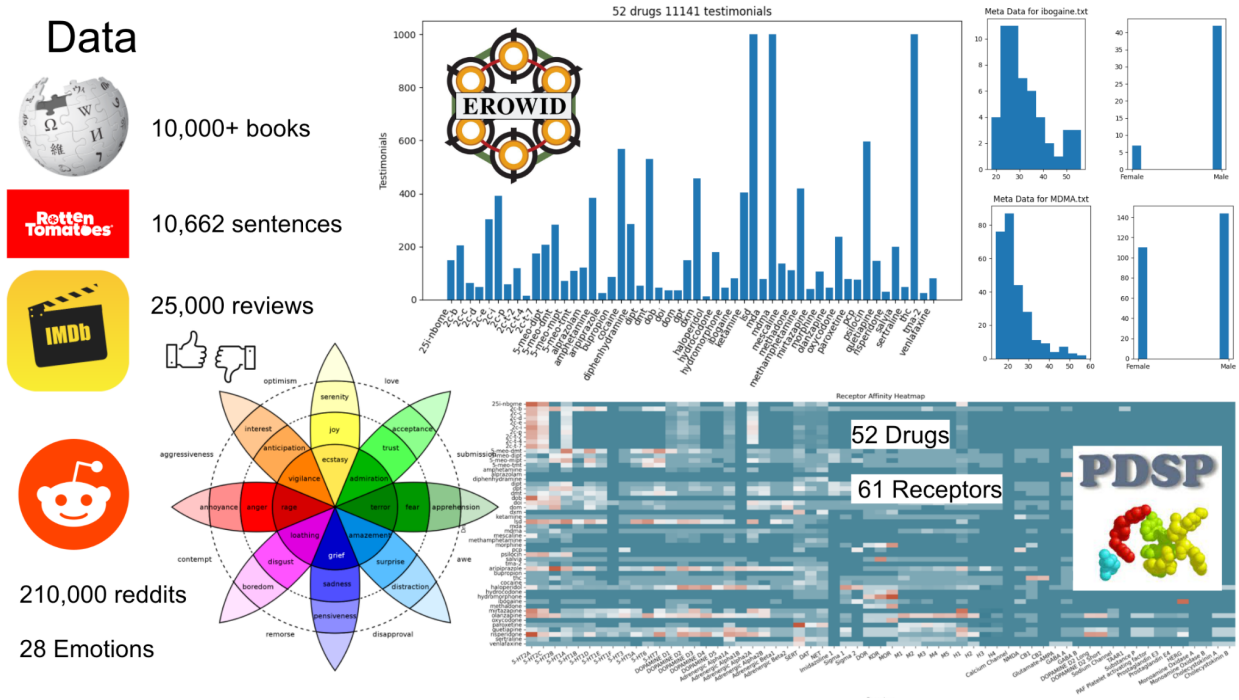


Figure: Receptor Affinities

Transformed receptor affinities for the 52 drugs and 61 receptors in the study, sourced from (36, 37).

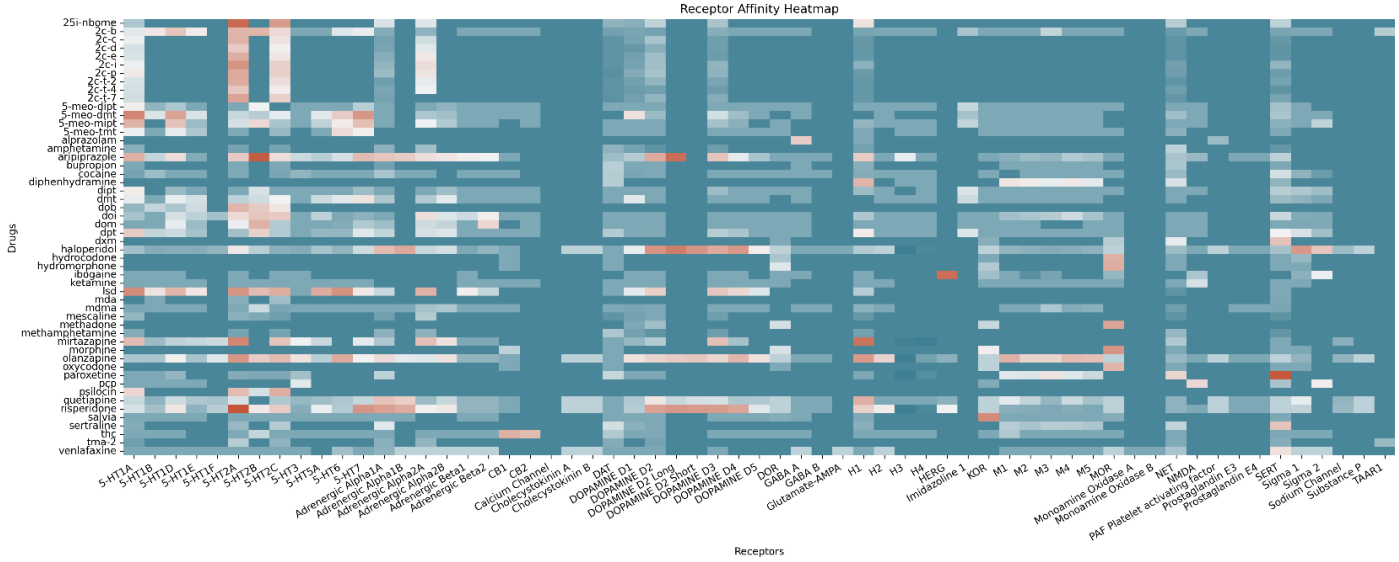


Figure: Drug Classification Performance

Test-set areas under the precision-recall and and ROC curves as well as confusion matrices for pharmacological class, chemical class, and individual drug labels are shown here.

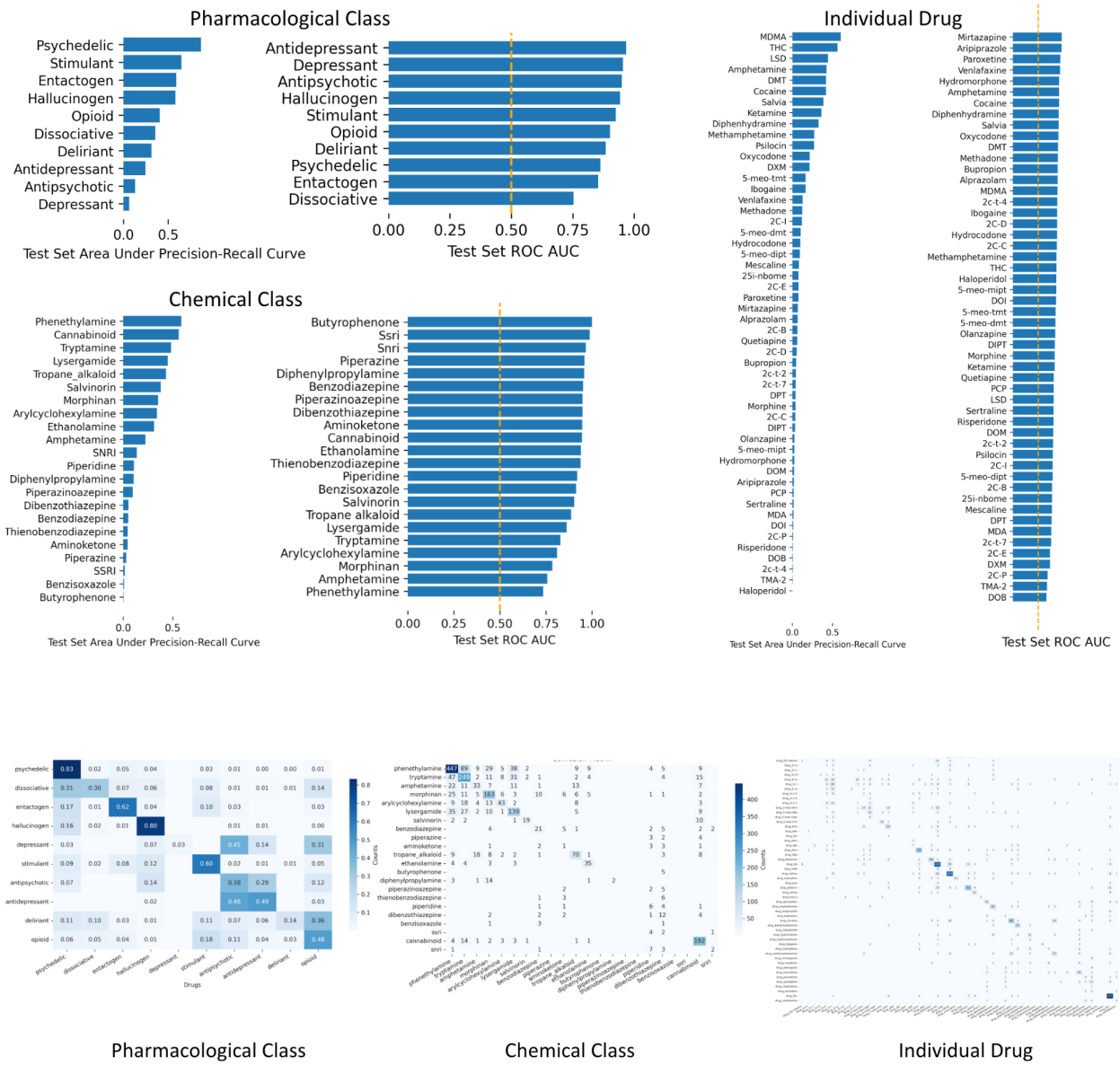


Figure: Single Task vs Multi Task BERTowid

Comparing single-task or multi-task BERT transformer models for BERTowid, it was found that they had comparable performance across drug pharmacologic classes as demonstrated in the

AUC for Precision-Recall chart below; given the minimal difference, a multi-task BERT was used for drug class prediction. For sex prediction…

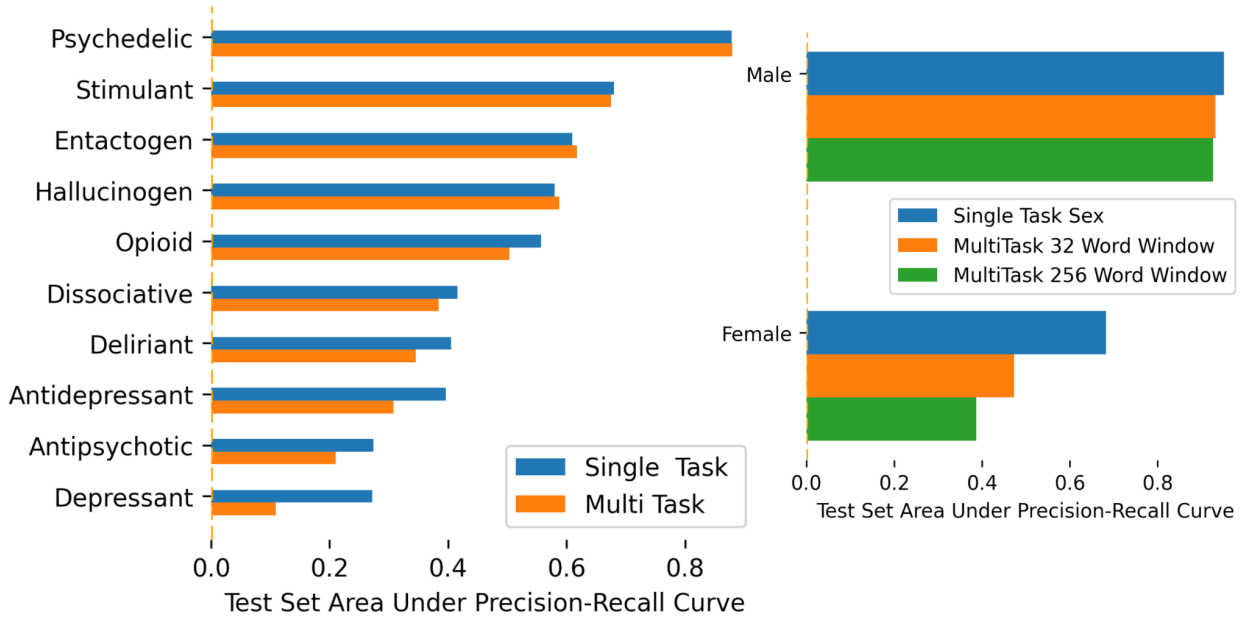


Figure: BERT Encoder Weights Comparison

To ensure optimal performance, standard BERT encoder weights were compared weights from SST2 and comparable AUC for Precision-Recall was comparable, and SST2 weights were ultimately used for the entire BERTowid analysis.

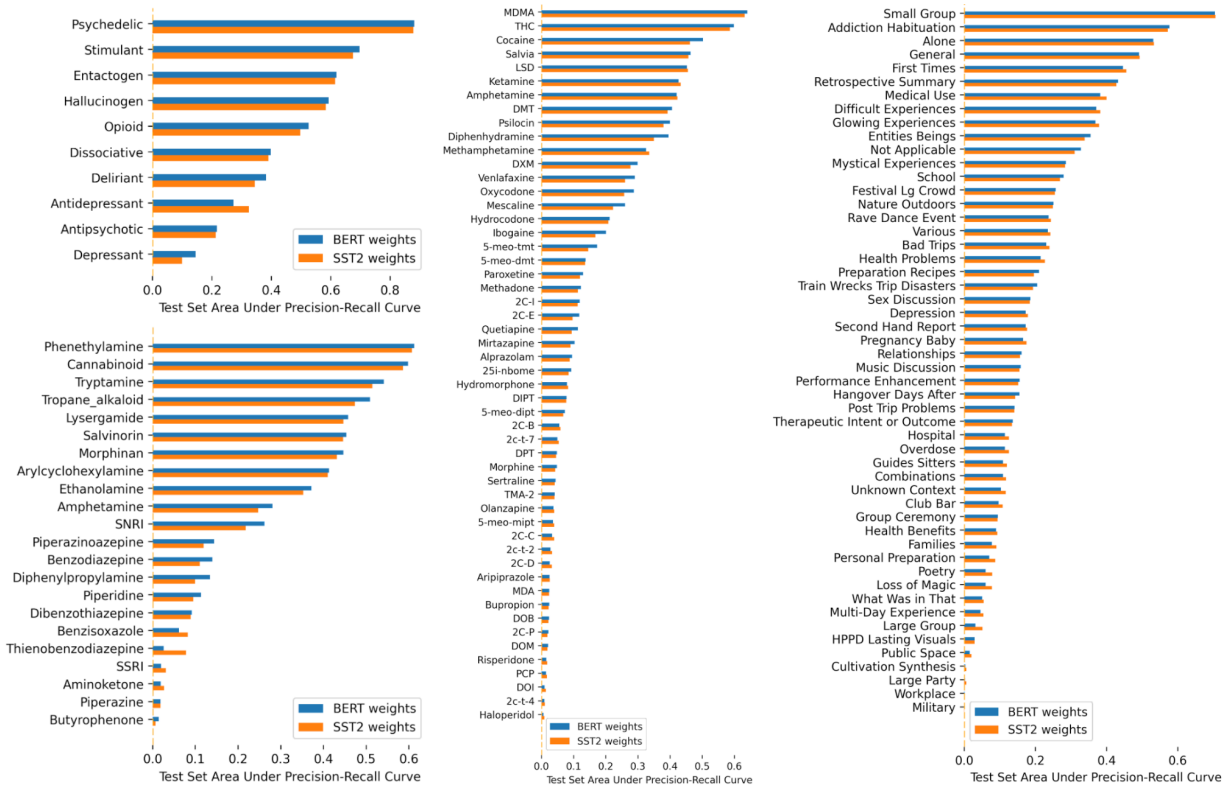


Figure: Cross Entropy Class Imbalance Weighting

To control for significant class-imbalance in the numbers of testimonials per drug, a weighted cross-entropy procedure was tested as compared to simple cross-entropy. It was found, as shown below, that while weighted cross-entropy had a modest effect on improving the AUC for Precision Recall for the drugs and drug classes with fewer testimonials, this was outweighed by the poorer performance on those drug classes with higher numbers of testimonials. Therefore, normal cross-entropy was used in this analysis.

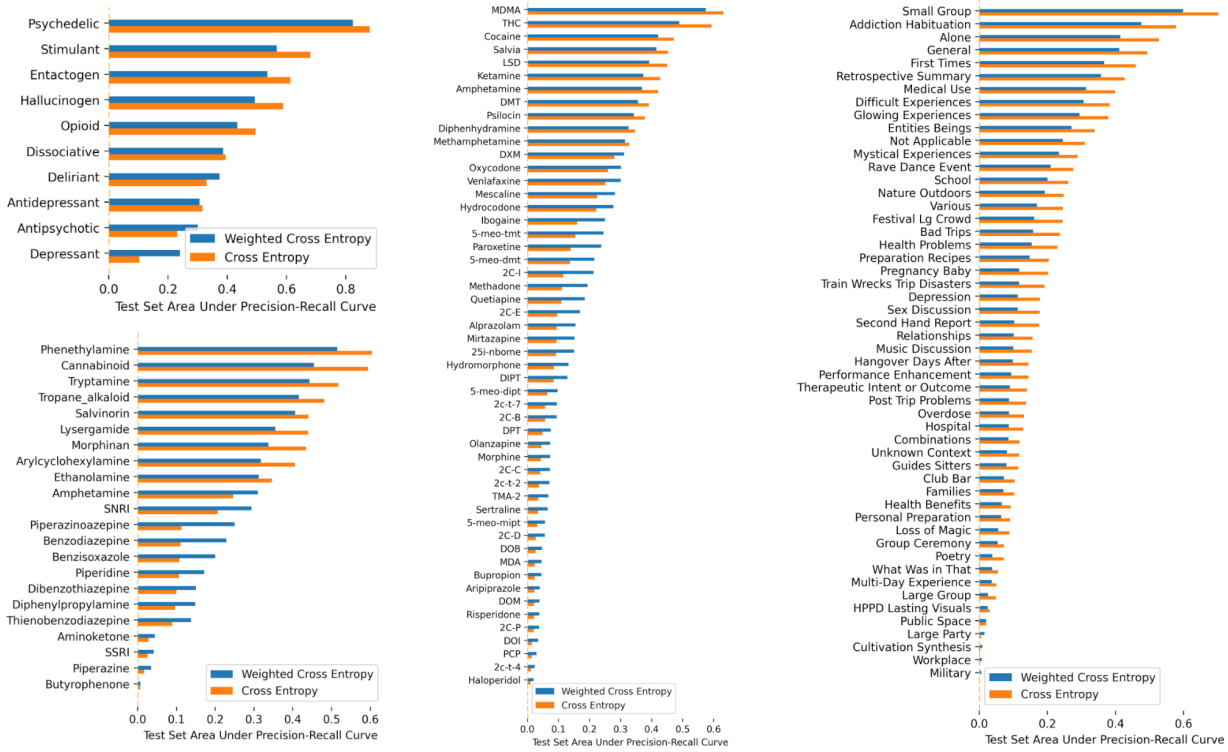


Figure: Word Window Size Comparison

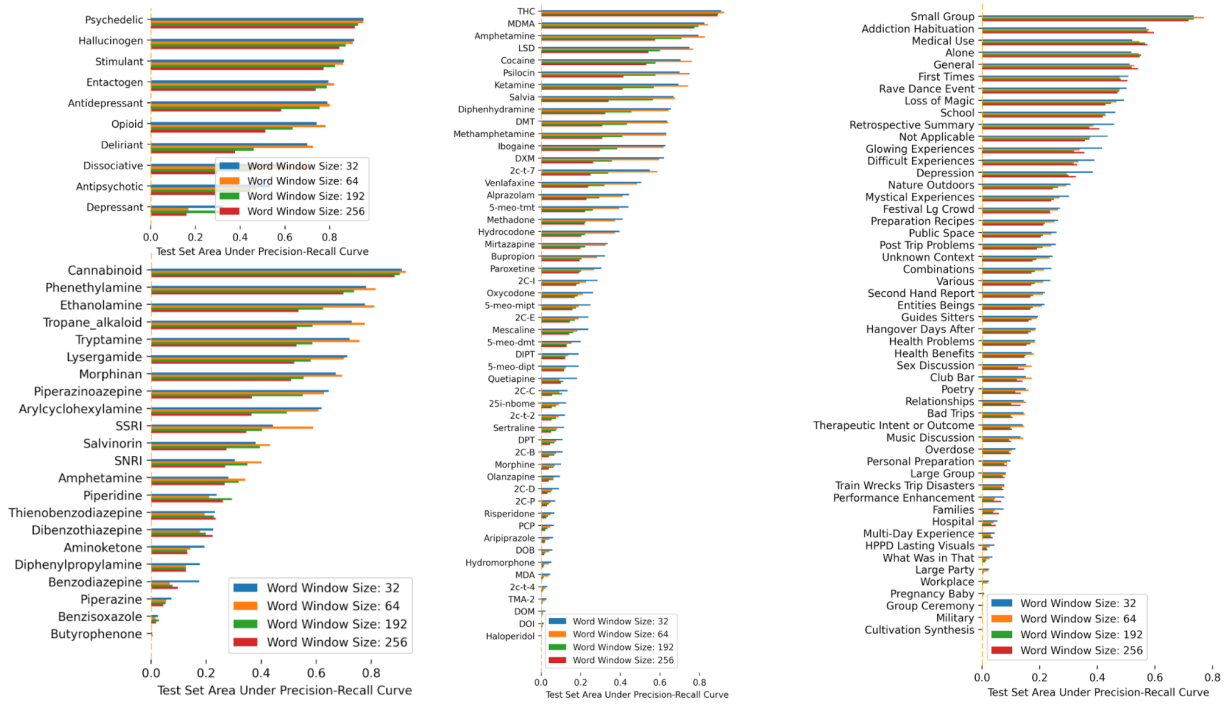


Figure: Dropout Rate Comparison

Dropout rates of 0.2, 0,5, and 0.7 perform similarly with best generalization results at 0.5. The learning curve comparison at far right shows the multitask loss at the end of each training epoch for the training set in blue, and the validation set in orange. Notice how increasing the dropout rate delays overfitting. The test set area under the precision recall curves are computed from a separate hold out set distinct from the training and validation testimonials.

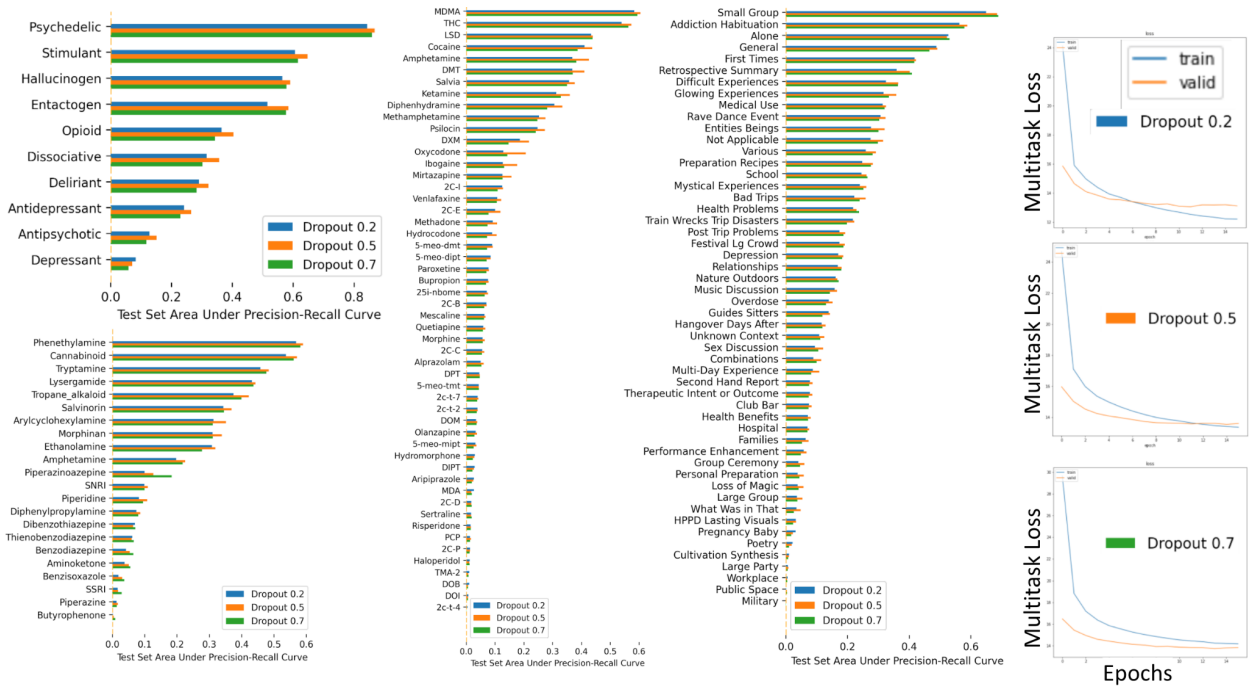


Table: Extreme BERTiment

Below are the highest and lowest ranking ~32 word testimonial-windows for each of the 28 sentiments. The unmistakable clarity of sentiment contained in both the sentiment label excerpts and also their opposites suggest that BERTiment is describing meaningful sentimental valences in both the positive and negative directions for all 28 dimensions of analysis.

sentiment	drug	text
admiration	2c-e	It was amazing and incredibly powerful. And the visuals continued to grow in scope and magnitude seemingly every minute. Eventually, everything became in constant motion and all objects were continuously undulating and before our very eyes.
not_admiration	2c-t-4	I didn’t know where I was or how I’d gotten there. I didn’t remember that I’d taken DRUG and I didn’t remember anything that’d happened earlier. Somehow I got it in my head that I’d died and was in a waiting room, waiting for my soul be judged and sent to either Heaven or Hell.
amusement	25i-nbome	At one point I felt it was as if Jesus telling me I turned on him. But then I laughed at him and the idea. No offense to any christians reading this. I don't hate jesus, it was just a crazy trip lol.
not_amusement	haloperidol	There are other effects I've been noticing lately, perception-wise, but it is extremely difficult to describe them with words. These include psychological changes, namely a more objective perception of feelings and emotions in one self and other people,

		which is both positive and negative since it involves a degree of detachment from people, which some might consider dangerous or conflictive.
anger	thc	How DARE he. What the FUCK was he thinking – not telling me what the fuck I was smoking. I was going to tell him off the next time I saw him – no – punch the bastard out – kill him?
not_anger	risperidone	Of all the many substances I've consumed, Matrix is still my favorite.
annoyance	amphetamine	When I'm disturbed while I'm trying to get work done on DRUG I immediately want to tell that person off so they'll leave me alone and let me work. If my concentration is broken, it is really annoying.
not_annoyance	risperidone	The following day, I was invited by my friend to a concert in our area, at a large amphitheater, with a well-known band as the headliner. I was a musician in a band for many years and I've attended quite a few shows, including a couple at that same venue, so I was excited and looking forward to this day.
approval	5-meo-dmt	I agree, but I would start with tasters when I was sober if I'd never been there before. the Teafærie
not_approval	tma-2	What day of the week was it? How does a day fit into a week? A week into a month? A month into a year? A year into a century? A century into history?
caring	amphetamine	Stay safe friends!
not_caring	aripiprazole	Maybe it's the reptilian brain exercising it's serpentine nature... I'm not sure at this point. I turn on my TV at 9:00 p.m. EST, Cartoon Network, Scooby Doo, one of the movies too. Can't remember which one, but I find cartoons in this state VERY startling.
confusion	thc	Eventually I started becoming very confused. All of the music they were playing in the background was really standing out to me and I had no idea what the episode was about. Hell, I couldn't even tell what the jokes were.
not_confusion	tma-2	Happy travels friends.
curiosity	dxm	DRUG DRUG DRUG Something to do with a Chandelier? I have had three or four previous DRUG experiences, but I wanted to try a higher dose so to get to the third plateau out of curiosity.
not_curiosity	haloperidol	Music is my canvas.
desire	2c-i	I just could not resist hunting some porn and pleasuring myself. I wish I could have shared the experience with a female. The sexual energy was so intense, I could vividly fantasize about what I wanted.
not_desire	risperidone	Increased muscular tension, especially prevalent in facial area, including tightness of the jaw. OEVs becoming slightly apparent. 11:00 (T+02:00) Heavy OEVs, full visual distortions and multitude of tracers. Sparkling of colors throughout visual field, especially reds greens and blues.
disappointment	2c-t-7	Still, the DRUG seemed to put me in a good mood and it wasn't at all unpleasant to be in a club environment. The DJ stopped spinning at 1:30 a.m and I was disappointed that things were ending so early.
not_disappointment	risperidone	So I'll leave it at that. This has been my shamanic initiation. It was a pleasure sharing it with you. As Terence McKenna said, a Shaman is someone who has seen the beginning and seen the end.
disapproval	bupropion	I wouldn't even suggest trying this drug, it doesn't seem to have any positive effects.
not_disapproval	venlafaxine	See you all there x
disgust	5-meo-mipt	20:30 – Eat ~7mg of DRUG (scale was fluctuating slightly between 6 and 7 milligrams). Tastes disgusting. For 7mg of DRUG this shit sure is strong. Tasted similar to DRUG but it was even more bitter.
not_disgust	haloperidol	In the morning, everyone who had participated in the ceremony visited with each other and shared some of their experience. I sought out Sharon to thank her for standing in for me and accepting Prem Das's gift.
embarrassment	psilocin	Embarrassed to be acting so nuts in front of my friends and not wanting to affect their trips, I turned to face the back wall and leaned forward onto the bed standing now while tightly grasping the sheets as the wave overtook me.
not_embarrassment	risperidone	Also highly interested in virola now! Deep thanks to those who made this long-wished-for experience manifest.
excitement	2c-c	She told me to call her around 2:30 to let her know how I was doing. I can't wait for 2:30. I was so excited. The drug had already started to manifest itself. I felt the normal stomach clenching I do on every DRUG I have tried.

not_excitement	2c-t-4	This DRUG is grossly misunderstood and understudied.
fear	mda	go away. This frightened me extremely, as I was afraid of getting rabies if it attacked me. But I seemed detached from my fear and instead watched it for several minutes (if it was even there).
not_fear	haloperidol	Either way, I greet you with: Namaste.
gratitude	psilocin	“Thanks, for bringing me back to awareness of the others in this house. Thank you all, for existing, and not-existing with me, and having this experience. I mean, it’s really quite profound, don’t you think?
not_gratitude	haloperidol	For example, the ceiling would come apart in abnormally-shaped sections and each section would raise up or lowest slightly so that they were all at different heights, and then they would shift around to gently overlap each other.
grief	ketamine	I saw paramedic's put me in an ambulance and take me to the hospital, I saw my family and friends standing around me, and I saw my grave. I thought to myself 'So this is death.
not_grief	haloperidol	“Intrigued and Interested” is a better descriptor: moreso than other substances in the past. We each had two coffees (t-4:00), 8 keto mini pancakes for breakfast (t-2:00), one Rockstar each (t-1:00), plus our normal regimen of supplements.
joy	alprazolam	Euphoric and feeling great. Even nodding a little bit, but not the kind of nod that makes me want to go to sleep, just nod and enjoy it. 7:45 Really talkative and happy, feeling the effects of everything, mostly the DRUG though.
not_joy	mirtazapine	but it's not the material itself, what's dangerous, but the people who and how use it.
love	psilocin	I love you I love you I love you I murmur, saying it as the world to myself as myself to the world, begging for forgiveness and comforting with infinite love, a lover in passion a throwaway comment to a friend a parting kiss a greeting touch, I love you I love you.
not_love	doi	After several minutes of debating back and forth how easily I could hide my obviously impaired state, the man left; he turned out to simply be a cable television representative making a cold call.
nervousness	5-meo-mipt	I was feeling very tight chested and uncomfortable, so I smoked a bowl of DRUG to take the edge off. I found my mind wandering quite a bit, and worrying about how the rest of the trip was going to progress considering how high I had already become.
not_nervousness	haloperidol	He now has more of a respect for Salvinorin A.
optimism	methamphetamine	I didn't graduate high school, so I live off on disability. This hopefully concludes my somewhat brief history about myself, and I hope it helps in any kind of way - by increasing insight, learning something, etc.
not_optimism	olanzapine	HOW DARE YOU? This is a voice from within, spoken so loud it shakes me, and I projectile vomit the contents of my stomach, watery acidic technocolor psychedelic yawn, I am crying. HOW THE FUCK DARE YOU VIOLATE THE HOLY?
pride	amphetamine	I got her some water and told her I know how she feels. I felt so proud of myself for turning it down, and without seeing the consequences of messing up my life I would have never been that strong.
not_pride	haloperidol	A sizeable number of audience members had apparently asked the network to conceal their identities (lol) so their faces were blurred out; the collective effect of these things was, at the time, incomprehensibly disturbing.
realization	lsd	All of the repeating patterns I had observed in nature made me realize that things repeat over and over again. I thought about how much Fleur looked like my first girlfriend, over 20 years ago, and realized that there were only so many ways to make hands, arms, a face.
not_realization	mirtazapine	Good luck and happy tripping everyone.
relief	mdma	N held all the pills, so I wasn't worried about security. After a quick pat down, we were free of the crowd and the temperature dropped by 15 degrees. It was a relief to be able to move freely again and my mood slowly improved.
not_relief	mirtazapine	Why is it a chair? What makes a chair a chair? Where did the idea of a chair come from? Chair, that’s a funny word.” The processes of my mind could not keep up with all the questions I had and everything I wanted to know.
remorse	hydrocodone	I essentially felt nothing other than the DRUG high, although I did feel very guilty for my outburst previously in the evening. I apologized profusely in the car and blamed it on the Vicodin.
not_remorse	risperidone	My friend and I made our way to a secluded spot in a this wildreness park. The spot was cool, totally covered by trees, there were tons of branches intertwined in a dome shape, and a log for sitting on.

sadness	lsd	I pick up my glasses to put them on and the asymmetry of my head is enormous. I feel my teeth grind against each other, feel how much my body spirals, and I'm sad.
not_sadness	haloperidol	She listened to every word that I had to say, and nodded with understanding. I marveled at how well we were communicating. Whenever I spoke I knew that I had her full attention, and in turn, when she spoke I listened to everything that she had to say.
surprise	lsd	I was shocked. I asked her, “So this was all a trip?” She told me that it was. I was shocked and almost disbelieving. I couldn’t believe that a simple drug had been the culprit of this madness.
not_surprise	2c-d	We had the following selection: Tool, A Perfect Circle, Smashing Pumpkins, Appleseed Cast, and some other prog rock. For anyone unfamilar with the musical experience on MDA,I recommend choosing anything that you like, don't get stuck with anything too abrasive or annoying.
neutral	morphine	-high timer
not_neutral	haloperidol	Thank you. Thank you. I love you. Love and Blessings Always and Forever.

Table: Extreme BERTowid

Below are the highest and lowest ranking ~32 word testimonial-windows for each of the 35 tags learned by BERTowid. The precision with which each tag matches the meaning for many of these passages flagged by BERTowid–and also their opposites–suggest that these descriptions are meaningful in both the positive and negative directions for several dimensions of analysis.

tag	drug	text
Small_Group	psilocin	I think it will be helpful if you are contemplating trying DRUG or are just reading about other peoples' experiences. Here we go... P and I were both 16 years old at the time and had never done shrooms.
Not_Small_Group	2c-i	I woke up on the third day of a four-day music festival, slightly hungover and groggy from a batch of DRUG I had taken the previous morning. After a brief wakeup period going through the motions of dressing, tooth brushing, etc, I decided to finish off a batch of DRUG I had been sold the previous day.
General	ketamine	Good thing I didn’t DRUG it with that dirt. I located the muscle (vastus lateralis) and relaxed it (DON’T flex it while injecting). The site was cleaned with DRUG and I found my self sitting with a DRUG ready to inject.
Not_General	cocaine	It was a temporary fix. It changed nothing about me. It did not improve the quality of my life. To put it simply, it was a fake, empty experience. It was a temporary fix.
First_Times	cocaine	So before long a guy friend of mine asked if I was interested in trying some DRUG I said sure. Let me give y'all a little more background on myself. I'm a staight A student, I'm on the honor roll, I'm on the debate team, and in many clubs at school.
Not_First_Times	lsd	Indulging in one of these sins often leads to you indulging in another, then another, then another, and eventually all of them. All these things have a web effect. Problems in one area resulted in problems in others.
Alone	psilocin	I stood up and opened my closet, withdrew my DRUG pipe and consumed deeply. I sat down in the dark again, I felt better, though now I decided I better take this lying down.
Not_Alone	2c-e	Me and my boyfriend both were shaking and we were bouncing our legs and our legs started shaking so fast it was like they were machines we were just witnessing shake like mad. The shaking almost felt involuntary because if we didn't shake everything was just painful.
Difficult_Experiences	dxm	He asked me 'Why did we do this?', and I could not answer. He then said 'This is the worst experience of my life'. I was thinking something along the lines of 'Oh it's not THAT bad.

Not_Difficult_Experiences	mdma	and doing as much research on E and all its permutations, effects... I started a daily program of DRUG in the morning, with Gingko Biloba or St. John's Wort, followed by DRUG and Valerian at night before bed.
Glowing_Experiences	ibogaine	DRUG DRUG Married, female, age 42. 115 pounds 19 months detoxed from DRUG muscle relaxants & DRUG anti-depressants DRUG Fanatic since August of 2009. Longest trip of my life to date - 14-16 hours Ever since I “broke my head” in December, 2009 with a series of extremely rough DRUG breakthroughs, I have had this nagging and oppressive thought that my death is near, sometimes imminent.
Not_Glowing_Experiences	dxm	I don’t remember all that well, but I got myself into the same type of situation. I figured, hey, I’ve dropped DRUG a few times, I can handle a DRUG binge. Well, all that I really remember was being attacked and defeated by a demon by the name of Rez.
Retrospective_Summary	mdma	To put recent events into perspective, my DRUG history started off with a bang eight years ago at the age of 21. I continued experimenting with it once or twice a month for the next six months culminating in the realization that the destructive effects were increasing and overtaking the beneficial effects with each new visit.
Not_Retrospective_Summary	diphenhydramine	I had parked my car half-way on the sidewalk with the windows down at 3am. It was only 3 blocks from where I had ended up. My money was miraculously still there, sitting all over the seat.
Various	2c-i	At around 5 am, I was walking around my house, and I started noticing that the place was an absolute mess, which never seems to really touch me when I have people over, but that day it did.
Not_Various	methamphetamine	There is no accompanying orchestral orgasm of consciousness, you just suddenly realize that you've accidentally crept into this new dimensional level of consciousness. And it is here that you will experience The Others, though we will refrain from commenting on this aspect until the need for subsequent missives on the subject arises.
Unknown_Context	5-meo-tmt	Mild nausea about 1 and a half hours after dosing. Nausea lasts for about 2 hours and is temporarily relieved when gases leave the body. After the nausea passes, the familiar stomach feeling of DRUG sets in - not quite nausea, just an indescribable odd feeling that is easily ignored.
Not_Unknown_Context	ketamine	DRUG DRUG DRUG DRUG Background: Healthy, casual psychonaut. Average diet and exercise. Prior familiarity with a wide range of psychoactives spanning ten years of use. Set/Setting: I'm in my apartment with one of my roommates.
Mystical_Experiences	psilocin	I lost myself in the ebb and flow of the universe and I was home. I could go on for hours and hours, and have before, about the wonders of my awakening, but truly, words don't exist for what I was experiencing, so hopefully my meager attempt at explanation will do.
Not_Mystical_Experiences	methamphetamine	I started attendin NA, Narcotics Anomynous, meetings 4 or 5 times a week. My life today is DRUG free. I havent touched it in a little over 2 months. I'm alot happier off of it.
Health_Problems	thc	I then consumed 3 more the next morning, and that was it. This was about 6 weeks before the experience I am writing about here. other then this I have had local anaesthetic twice, once for repairing a broken tooth, and once for stitches to a cut.
Not_Health_Problems	2c-e	I was unconcerned about any other humans, I felt that I was alone in this new dimension and yet I was in awe and mostly unafraid. My destination was the park, a rather large one comprising 3 open fields, trees on the border and some children's play equipment.
Combinations	dmt	No problems.
Not_Combinations	psilocin	The walls and ceiling were breathing in and out together to a great degree, and everything on my wall was 3-D. People came out of the wall, and a space shuttle was in constant flight, flying past stars and galaxies, in a poster where it is just taking off.
Not_Applicable	cocaine	The first binge lasted 2 or 3 months within the first week of using I lost 15 pounds, I thought I found my answer to everything in life just a simple line, a quick fix and everything was all right.
Not_Not_Applicable	mdma	He was completely sober at the time, but had an 18 of beer in his trunk and we had 5 e pills along with some DRUG a few bowls. We just kept calm and explained it off, and the cop just told us to get where we were going and stay there.
Bad_Trips	lsd	All my lives were the same from beginning to end. I did the same things and got the same ending. Looking back at it, I realize that it was true insanity that I experienced in my bad trip.
Not_Bad_Trips	5-meo-dmt	At the beginning of the ceremony we were given the space to request what it is we wanted from the medicine. I didn't take this lightly, most of my group and many others got exactly what we asked for and to a major degree.
Hangover_Days_After	2c-b	returning home.

Not_Hangover_Days_After	thc	It is quite useful actually, that I am able to see all the keys and the screen at the same time. God, those fingers are moving fast and make a fun little dance on the keyboard!
Entities_Beings	mescaline	Closed eyed visuals are beyond amazing. I seem to have met a Peruvian shaman and my body/soul is filled with brilliant purified white light. I am seeing closed eye visuals of the shaman and then the vision switches to someone who seems to be in Tibet.
Not_Entities_Beings	alprazolam	At about T+45 began to feel the effects of the drug. Mostly a mild stoning effect, but motion seemed incredibly interesting. I left the group I was with (always a bad idea when on a new substance) and went to hang out with some of my other friends who were drinking.
Music_Discussion	5-meo-dmt	Life is good.
Not_Music_Discussion	oxycodone	(meaningless term unless youre a shooter I know) It resembled mud, but I managed to get the shit in the DRUG after some work. POKE, ASPIRATE, BURNING VEINS, ENDORPHIN EXPLOSION, BLISS, COLLAPSE. Thats the jist of it, but I lived.
Addiction_Habituation	methamphetamine	I will always have a problem coping with my problem. I went through so much pain and suffering (not to mention the pain I put my family through) due to my addiction.
Not_Addiction_Habituation	cocaine	I was ready to take a little walk alone and after getting dressed followed the advice and took a couple of big bumps off a key. I chilled out for a few minutes expecting something insanely euphoric and almost spiritual.
Post_Trip_Problems	Salvinorin A	I took the third hit, holding all of it deep in my lungs. Then NOTHING. I lost consciousness. What I gathered from the first hand account of friends was that I stumbled around very clumsily.
Not_Post_Trip_Problems	tma-2	Back home (0:25 pm ie I checked my pupil and it was still dilated although only moderately so. I had expected to be baseline after 8h, so occupied myself until 1:40 am expecting to be out of the experience at that point.
Nature_Outdoors	lsd	Straight ahead was the DRUG clear ocean, sandy beaches and creamy white clouds of the 'east-side,' while directly behind us was the immense green landscapes of the thick Hawaiian jungles and it's dark, looming rain clouds.
Not_Nature_Outdoors	amphetamine	The sad thing is though, I like DRUG ALOT. And even though this happened to me today, I don’t know if I’m going to have enough will power to stop taking it. It’s not as if the drug is addictive in such a way that your body feels it needs it to function, it’s more like a mental drug.
Relationships	ibogaine	My family have lived for generations in the Caribbean, unwittingly participating in - yet outwardly shunning - the subversive caste system. I accepted it unquestioningly, at home being an unspecified outcast in my society, marked by my skin and my eyes, my base state subtly asserted as that of an ‘oppressor, an outsider’ while in truth my childhood identified me as the oppressed.
Not_Relationships	thc	- But then-- ALL thoughts are hallucinations! At that point I would convulse involuntarily. From somewhere deeper in my brain than logic, I saw an infinite loop of thoughts stretching into darkness ('Then that statement, too, must be a hallucination!
Depression	mdma	DRUG DRUG DRUG For years I've experienced various levels of depression (3 years). For the first 2 years I was diagnosed with major depression after two attempts at my own life. I sought treatment and was put on zoloft.
Not_Depression	dmt	They arent making it up, it is really there. It just doesnt have the same dimensions as this 'real' world. The efficiency of there seemed immaculate. Everything was in perfect time/tune and there was, dare I say it?
Therapeutic_Intent_or_Outcome	lsd	DRUG catalyzed the first major shifts in my spinal structure and gave me the experience of a straight spine, providing me with hope, encouragement, and wisdom that strongly impacts my mental experience of my body in everyday life.
Not_Therapeutic_Intent_or_Outcome	5-meo-mipt	Very nice... I can see how some might compare this to the DRUG DRUG I feel that listening to some music, laid out, with my eyes closed would be pristine. I doubt it'll happen though.
Overdose	25i-nbome	I'm going to die anyways, so why let myself suffer?' I knew how I would have killed myself, too- I was going to get out of Chayla's house and lay in the street and wait for a car to hit me.
Not_Overdose	2c-i	This instantly brings some peace of mind back, I can feel the soft cradle of DRUG rock my hopped up mind softly back and forth. I feel secure in my abilty to discern between what is real and what is not.
Medical_Use	methadone	I had no time for a girlfriend, no time for my family, and definately no time to goto school even though it was my senior year. I tried an inpatient 30 day shit but that just put my problem on hold until I got out and then went into an IOP (Intensive Outpatient Program) that lasted a minimum of six months.
Not_Medical_Use	methamphetamine	So I tried it. I finally smoked some DRUG I took one hit of some good quality glass. It wasn't a large hit, I didn't

		feel much at all. I took another and began to feel alert and awake, as I expected.
Sex_Discussion	amphetamine	But be weary, shes a tempting mistress, who could possess you in a matter of weeks.*
Not_Sex_Discussion	methamphetamine	I was not overly keen to try it, as I tend to mainly enjoy a monthly or two-monthly dose of DRUG and don't feel I need any other drugs, having been down the psychodelics path over many years and becoming well and truly over them.
Train_Wrecks_Trip_Disasters	ketamine	I fell asleep soon afterwards.
Not_Train_Wrecks_Trip_Disasters	mescaline	The feeling of the DRUG is swimming happily through my body, a school of fish frolicking about, miles beneath the surface. Writing is flowing effortlessly and readily from mind to page. Very little editing is being done at this point.
Guides_Sitters	lsd	From the MAPS Bulletin - Volume 9 Number 2 Summer 1999 - pp. 11-14 ---------- Successful Outcome of a Single DRUG Treatment in a Chronically Dysfunctional Man Gary Fisher, Ph.D. ---------- Editor's Note: MAPS publishes accounts like the one below because they are reminders of the sometimes surprising powerful effects that psychedelics can have.
Not_Guides_Sitters	methamphetamine	Don’t expect your will to be greater than the will of DRUG It has pulled me in countless times despite negative consequences. I plan to quit using altogether soon however I am indulging tonight.
Rave_Dance_Event	mdma	The idea of such a drug disgusted me. However we went to a rave the following night and I dropped a mitsubishi. That was my first rave and probably my best. We were dancing in some guy's apartment until the early hours of the morning.
Not_Rave_Dance_Event	lsd	I love lysergic DRUG diethylamide, it is an unbelievably wonderful sacrament that has been bestowed upon the human race, and I truly believe that a direct experience of reality, beyond labels or concepts, could push the human race off the destructive path it is currently on.
Preparation_Recipes	morphine	*If you are not using plant material, skip this step* Both stems and pods can be used for their alkaloids, but being plants the quality is variable. It is best to harvest shortly after the petals fall from the plant and before the plant is flushed of its goodies become lost from the rain.
Not_Preparation_Recipes	mescaline	I speak to someone they tell me I'm five mile from my home. I believe I can make. I get back on the road. I feel like I am losing it.
Festival_Lg_Crowd	doi	Walking into the sea of people was an intense and disorienting experience, ACL is a big festival, there were thousands and thousands of people there all at the main stage, because almost everyone wanted to see Dylan.
Not_Festival_Lg_Crowd	methadone	After struggling slowly facing one thing at a time I managed to get my license back and got a car (nothing fancy I am saving for a corvette or the new camaro). I have a job as the senior chemist making serious money which I have managed to save a little of for emergencies.
Health_Benefits	methadone	First off, a little bit about myself. I have been using DRUG and opioids for 2 years non-stop to deal with pain resulting from a kidney condition. I've taken DRUG DRUG meperidine, DRUG propoxyphene, DRUG and now finally methadone.
Not_Health_Benefits	ketamine	So, no real worries going in. I was expecting something fun like mxe, especially since I had always heard of it in the dance and rave contexts. I was at my friend E's grandparent's house (they were gone and had left him the keys) and we were gonna try the DRUG recently procured.
Large_Group	dxm	and good night.
Not_Large_Group	venlafaxine	Having experienced both, I asked my new, smart, shrink. He said that the effect is a severe defficiency of serotonin as well as neurepinephrine, because the stimulus to produce more is gone and the brain hasn't gone back to producing enough of its own yet.
Multi-Day_Experience	dob	I pay him ten for two hits- half what he was asking- and promise that if and when I start to feel it I'll pay him the other ten. I stick em under my tounge and proceed to the show to beat people up for the next two hours.
Not_Multi-Day_Experience	lsd	Here comes five pairs of headlights! Yeah, the cab is here. We walked towards the van, waving it down. When it stops, we realize it wasn't a cab, it was a mom with a carload of kids inside.
Club_Bar	5-meo-dipt	The buzz increased a fair bit, and probably would have probably resulted in a pleasant experience had we not been in the very hot, crowded, noisy nightclub environment (it was Easter weekend so the club was unusually packed).
Not_Club_Bar	5-meo-dmt	(days later->) Now, This is where my tryps get interesting, Things that shouldn't happen, do. I have 2 digital clocks

		in my room, One with the correct time, and the other I plugged in 10 minutes after midnight, so that it would always flash the near correct time.