# Which acts model transitions between different happiness states?

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**Abstract.** We embarked upon a causal dive to explore acts leading to alarming drive towards self-destructive behaviors. Articulating the entire spectrum, ranging from recipes of long-term happiness to factors leading to self-destructive behaviors, we expanded the three state model of happiness states of people (G (lasting happiness), P (flickering) and I (frustration)) into a 9 stage model. Each of the G,P,I states is further expanded into G,P,I substates. This 9 stage modeling incorporates motivation/intent/human need in activities. Both causal inference and XgBoost classification of 54,066 user tweets revealed that: (1) excessive focus on Work, Money & Economy, Technology & Digital Life, Food & Drink, Politics & Society, Physical environment, Sports & Music & Public events; leads one to transition from G to P state. (2) excessive focus on personal or interpersonal struggles expressed in emotions; personal entertainment (movie, dream etc.), mental health issues leads one from G to I transition. (3) Transition from P to I is similar to that of G to I with the addition of excessive focus on Food & Drink, more individual relationships, slangs, criticism, envy, abuses.

**Keywords:** modeling happiness · motivation & acts · causal transitions

## 1 Introduction

Happiness is the most sought after commodity in this world and the most difficult to hold on to. Like wealth is prone to be squandered away so easily, similarly sustainable happiness is rare. Numinous activities can potentially drain away the experience of happiness. Every single act is like a debit or credit. Mental health problems, negative family dynamics, trauma, and addiction causally reduce happiness [1]. Financial stress or economic insecurity, lack of autonomy, social networks, and environmental stressors can detract from happiness [2]. The stronger our relationships, the more likely we are to live a happy, satisfying and healthier life [3].
Intent (motivation) and content (the qualities that a person is manifesting) decide the experience and affect state in various activities irrespective of the result. This also holds for happiness. Any activity of an envious, proud, violent, or angry person will increase misery and madness. When the motive behind an act

is self-obsessed enjoyment, fame and opulence, then the happiness achieved will be nectar in the beginning and poison in the end [5, 6].
M Bhasin et. al. [7] framed a three state model of happiness based on a longitudinal study of 159,632 Twitter users with tweet history spanning from Jan 1st, 2007 to Dec 5th, 2017. We expand on this work by incorporating intent (motivation, attitude) along with activities to understand the transitions between the three happiness states.
Through our study, we attempt to answer the following research questions:
RQ1.Can we leverage causal inferencing to get deeper insights into transitions leading to self-destructive behaviours?
RQ2.Can we expand the 3 stage model of happiness states to incorporate intent (motivation, attitudes)?
RQ3. Is the expanded model of happiness states consistent with the causal transitions ?

## 2 Related Work

Recent researches have used experimental designs such as vignette (hypothetical scenarios) and factorial surveys [8, 4], econometric modeling and experiments like randomized controlled trials [9], and the application of frameworks like potential outcomes [10] to make causal inferences about happiness. These methods allow researchers to estimate the true causal effects of health, income, relationships, and life events on happiness, moving beyond mere correlations to actionable insights. In the absence of experiments, researchers use observational data and statistical modeling (e.g., regression analysis, propensity score matching) to estimate the causal impact of various factors on happiness, while carefully addressing potential sources of bias and confounding [9, 11].
Multiple theoritical frameworks model human needs. For example Maslow's need hierarchy includes the needs for safety, belonging, esteem, self-actualization, and transcendence, but leaves out the needs for autonomy, immersion, achievement, identity-formation, fairness, and morality [12]. Pincus model of motivation spans human needs by incorporating four life domains (the domains of the Self, the Material, the Social, and the Spiritual) with three levels of attainment (To Be, To Do, To Have) for each domain.
We expanded the 3 stage happiness state model [7] into a 9 state model by incorporating human needs or motivation based on Pincus model of motivation [12]. The 9 stage model gives meaningful insights on what leads to transitions between the states. In addition, applying causal inference on the state transitions adds to those insights. These insights give a clear picture to a person about which directionality one is heading, so that one can take heed, well in time. Also, this approach provides signals for intervention at the right point, thus enhancing effective intervention strategies.

## 3 Dataset

The dataset used consisted of 29,398,974 happy tweets and 22,369,471 frustrated tweets. On average a user had 304.57 happy tweets and 231.75 frustrated tweets. About 40% of the users have less than 100 tweets. The details of the dataset and the steps of the filtration process are given in [7].After filtration steps the number of users whose tweets were fit to be analyzed got reduced from 159,632 to 54,066.

## 4 Methodology

### 4.1 Causal Inference

Every user's tweets were divided into two sets:

1. Tweets before the mean date time in the tweet dump timeline
2. Tweets after the mean date time in the tweet dump timeline

Some overall datetime characteristics of tweets are mentioned in Table 1.

Table 1: Tweet Datetime characteristics

| Metric | Value |
|---|---|
| Mean Start DateTime | 2016-12-07 07:16:48.22 |
| Mean End DateTime | 2018-10-10 12:08:38.75 |
| Standard Deviation of Start DateTime | 1255 days 02:10:37.99 |
| Standard Deviation of End DateTime | 701 days 14:03:02.77 |

Table 2: Happiness State Transitions

| Transition Type | No. of Users Transitioning | Propensity Score | Unadjusted ATE | Adjusted ATE |
|---|---|---|---|---|
| GG | 1275 | | | |
| GP | 797 | 0.385 | 0.19 | 0.18 |
| GI | 297 | 0.189 | 0.4 | 0.37 |
| PP | 1749 | | | |
| PI | 535 | 0.234 | 0.19 | 0.15 |

Each set for each user was evaluated for classification into G, P, I states. So, from this classification, the half-way transitions among the states were obtained, eg. from G to P or G to I or P to I. Each of these transitions were then taken one by one for causal inference. Causal inferences were drawn using propensity scores.

Propensity score estimates were obtained by logistic regression of the treatment on the potential confounders. The propensity score estimates are simply the predicted probabilities obtained from logistic regression. It gives the conditional probability of receiving the treatment. The goal is to obtain the best possible balance between treatment groups in terms of all pretreatment confounders. As an example, the group of users undergoing G to P transition is the treatment group, while that undergoing G to G transition forms the control group.

**Which confounders to include in the propensity model is important?** De Choudhury et. al. used unigrams and bigrams from Reddit to control for prior user behavior, performing propensity score matching [13]. Olteanu et. al. used top unigrams/bigrams from Twitter to control for prior word use in causal models (matching-based) [14]. K. A. Keith et. al. in a survey reviewed methods where text, represented as a unigram or bag or words, is used as a confounder [15]. Taking clue from the above we formated our approach as below:
Three separate bag of words for all G, P, I users respectively were made. Then we calculated the log likelihood scores of all unigrams. Now for GP transition, the confounders chosen were all unigrams in the intersection of top 15% P unigrams with bottommost 40% of G unigrams. The intuition is that those activities causing transition to P state will be prominent characteristic in the P state and its some traces will be seen in the G state. Likewise confounders were chosen for GI and PI transitions as well.

### 4.2 9 Stage Modeling of Happiness States

Pincus et. al. [12] developed a unified model of human motivation that integrates all prior "mini theories" of motivation into a single, symmetrical model based on first principles: four life domains (the domains of the Self, the Material, the Social, and the Spiritual) crossed by three levels of attainment (To Be, To Do, To Have). We developed our 9 stage model of happiness taking inspiration from the Pincus model of motivation.
To each of the G, P, and I states, we added 3 stages corresponding to three levels of attainment (To Be, To Do, To Have). From the Pincus model of motivation: (1) Self and Material domains correspond to the I state, (2) Social and Material domains correspond to the P state (3) Self & Spiritual domains and also Social & Spiritual domains correspond to the G state For eg. for state 'I', 'II' will correspond to the level of aspiring but not working towards 'Self & Material'. Struggling towards 'Self & Material' will lead to the happiness state 'IP'. Being established in acts towards 'Self & Material domain will lead to the state 'IG'. In 'IG' state acts of efforts toward 'P' state or 'G' state will also be seen. Similarly 3 state divisions for 'P' state and 'G' state can be defined.
State 'IG' also indicates directionality towards lasting happiness while 'II' indicates directionality towards self - destructive acts. Same for 'P' state.
Based on the definitions of the 9 states of happiness, classification of subcategorization of previously annotated 71 G users, 71 P users, and 71 I users

was undertaken. Each tweet was classified into one of the three subcategories, thus an I user was thus further defined in terms of ratio of IG, IP, II based on relative number of tweets in each subcategory.
Two annotators manually annotated each user tweet. They read all the happy and frustrated tweets from every user. Conflict cases were resolved by a third annotator. The Inter-Annotator Agreement (IAA) kappa came out to be 0.78.
We created a feature vector and tested using Xgboost for categorizing a user into one of the three modeled sub-states of happiness: G/P/I for each state G/P/I. Sample tweets for 9 happiness states are listed in Table 3.

The following is the list of the features we used:

1. Linguistic analysis: We used LIWC as a 64-dimensional vector (LIWC 2007) [16]
2. Three dimensions of word meaning: Valence (V), Arousal (A) and Dominance (D). VAD scores for each user were calculated using ANEW Lexicon [17]
3. Sentence to 348 feature value vector associated with the all-MiniLM-L6-v2 model, using S-BERT sentence transformer (distributional semantics) [18]

# 5 Analysis and Discussion

## 5.1 Causal Inference

This methodology led to the choice of 18672, 17254 and 27991 unigrams as confounders for GP, GI and PI transitions respectively. Counters were made for the selected tokens/confounders and the relative counts were used as feature values. Model Accuracy and ROC_AUC Score for GP, GI and PI transitions were 0.61, 0.81, 0.77 and 0.63, 0.70, 0.67 respectively. The model also ranked the features/confounders according to importance. The propensity score was used to adjust for confounding using Inverse Probability Weighting (IPW) and thus the adjusted Average Treatment Effect (ATE) was calculated. The unadjusted and adjusted ATE values for GP, GI and PI transitions are given in Table 2. The word clouds for top 500 confounders for GP, GI and PI transitions are given in Figure 1.
Clustering Analysis: The common categories obtained from the clustering analysis of the features in GP, GI and PI transitions are Negative Emotions & Mental Health, Positive Emotions & Well-being, Social Relationships & Support, Religion & Spirituality, Daily Life and Routine (eg. job, sleep, weekend, friday etc.), Communication & Social Media, Entertainment & Leisure, Health & Wellness, and Celebrations & Special Occasions. The categories which are more prominent in GP transitions as compared to GI transitions are Food & Drink, Physical Environment & Nature, Technology & Digital Life, Politics & Society, Self & Personal Development, Work, and Money & Economy.
In GI transitions, clusters around mental health, emotions, and relationships are dominant, with strong representation of both negative and positive states. In GP transitions, Work, Money & Economy and possibly Technology & Digital

Table 3: Sample Tweets for the 9 Stages of Happiness

| Stage | Sample Tweets |
|---|---|
| GG | 1. I'm so glad that God is restoring a healthy co-parenting relationship between my son's father and I! We put our petty differences aside for OUR son and are becoming what we once were...FRIENDS! After our breakup it was rough but God answers all prayers.<br>2. i am so thankful for my job and the people i work with ! they are so genuine . i don't know if it's because they're all counselors , but i'm so glad i was put in this position .<br>3. one of the things i keep learning is that the secret of being happy is doing things for other people. |
| GP | 1. Stop worrying about what others say. If it makes you happy, go for it. That's how I'm choosing to live my life.<br>2. hurting today ! but hiking up the hill; sledding in the snow was so worth it. pure joy !<br>3. writing books for kids is my favorite thing to do . it gives me pure joy . allow me to get woo for a minute , i truly believe that educating the next-gen about how systems work and how they can transform the world |
| GI | 1. I'm so happy people can't hear what I'm thinking. Right!<br>2. we are asleep until at least 11:00 am @abc for the last few years ; long gone are the days of rope drop; family miserable all day long . so tom , i get to live vicariously through you for the beautiful sunrise photos ! we do enjoy the gorgeous sunsets around crescent lake though !<br>3. @abc would be better if i could actually spend the day with him but doing all i can to remember happy things - getting sucked into sad |
| PG | 1. @abc being sick is awful . i 'm glad it 's coming out instead of nasty sneaking down the back of your throat though<br>2. i 'm done being upset . being afraid . being anxious . being sad . i see him , always these things . no more . no mas . life is too short . let all the bullshit go and be happy . instead of " live a little , " " live a lot ! " be free and spread positivity .<br>3. in any case, i 'm happy in my new post, i 'm looking forward to a bright future here and if i 'm ever in a position where i 'm doing the hiring, i 'll remember these moments. |
| PP | 1. @abc i generally feel very sad and lonely during the holidays . i am sorry for your pain . try to stay away from anyone who makes it worse , although i'm one to talk. you've been through enough toxicity in your life to go down that road again.<br>2. i don't remember ordering these but i 'm thrilled tbh???<br>3. anyways i found a low-carb cheese biscuit recipe and i'm really happy about that |
| PI | 1.i'm old, i'm tired, i'm sick of being disappointed by women in esports that could push back against these harmful or destructive behaviors and instead choose to embrace them<br>2. I am overjoyed he hasn't deleted this yet 2 crime on the internet<br>3. it ' s so sad that people that use to be around you everyday that ' s beneath you , will still speak on you because they mad they can ' t fuck with you ! |
| IG | 1. it's always great seeing my exes be happy with their new significant others<br>2. treasuring the happy pockets of time i get<br>3. i decided to keep a gratitude journal in 2019 and write down 3 things a day that made me happy ... 10 days in and i am already slightly ashamed by how often my cat and tasty food have featured . lol |
| IP | 1. Glad I'm like me and not like them<br>2. All I want is to be happy...<br>3. was having a nice leisurely lunch alone then open my tele chats idk why suddenly i feel so frustrated and insecure argh stupid |
| II | 1. my wife was just wondering yesterday why my memory is so horrible . now it makes sense because i ' ve struggled with severe anxiety and depression for years<br>2. this has got to be the saddest generation ever . all they do is bash each other , point fingers , brag about how they hate the opposite sex , and cry themselves to sleep every night . then they wonder why they ' re so depressed ...<br>3. i 've had a bad few days . depression is a bitch and makes me think all kinds of fucked up things . today is a new day though and i feel less crappy so yay ! |

Life are more prominent, and perhaps less focus on clinical mental health terms. Food & Drink, Politics & Society, and Physical Environment & Nature are minor in both but may be slightly more present in GP transitions. PI transition features are similar to those of GI transitions but more prominent on Food and Drink and less on Religion & Spirituality.
Results of open coding analysis for qualitative clustering for GP, PI and GI transitions are enlisted in Table 4. From the results we can infer the following:

Fig. 1: Word Clouds for top 500 confounders for GP, GI and PI transitions


(a) GP factors


(b) GI factors


(c) PI factors

Table 4: Comparison of Open Coding Categories Among Different Transitions

| **Category** | **GP** | **PI** | **GI** |
|---|---|---|---|
| Positive Emotions | 52 | 49 | 49 |
| Negative Emotions | 41 | 57 | 54 |
| Social Relationships | 38 | 36 | 38 |
| Achievement/Performance | 24 | 18 | 19 |
| Daily Life & Routine | 35 | 29 | 31 |
| Communication/Social Media | 29 | 27 | 28 |
| Entertainment & Leisure | 23 | 18 | 18 |
| Food & Drink | 12 | 8 | 7 |
| Spiritual/Religious | 8 | 9 | 8 |
| Miscellaneous/Other | 38 | 41 | 40 |

1. Emotional Content
   All three transitions are rich in both positive and negative emotions, but PI and GI transitions have a slightly higher count of negative emotion words, indicating more personal or interpersonal struggles, while GP list is slightly more balanced.
2. Social Relationships
   Social/family/relationship words are strong in all lists, but GI and GP have slightly more references to collective or group terms (team, fans, friends, couple, etc.), while PI list leans more on individual relationships.
3. Achievement/Performance
   GP list has more words related to achievement, performance, and competition (score, win, champion, runs, performance, proud, etc.), reflecting a broader inclusion of sports and public achievement terms.
4. Entertainment & Leisure
   Present in all, but GP list includes more references to sports, music, and public events, while PI and GI include more personal entertainment (movie, book, dream, fun).

### 5.2 9 Stage Modeling of Happiness States

The number of manually annotated tweets for GG, GP, GI, PG, PP, PI, IG, IP, II are 234, 56, 74, 48, 240, 57, 45, 154, 76 respectively. However, to make the classifier unbiased equal number of tweets were taken for G, P, I classifiers respectively. For G classifier 56 tweets each of GG, GP, GI were taken for training ans testing the model. Similarly for P and I classifiers 48 and 45 tweets each of PG, PP, PI and IG, IP, II respectively were taken. For Xgboost classifier for each of G, P, I users 70% training data and 30% test data split was performed. The accuracy obtained for G, P, I sub- classifiers were 65.4%, 60.5% and 59.0 % respectively. The confusion matrix of the G, P, I sub- classifiers are given in Tables 5, 6 and 7 respectively. The Precision, Recall and F1 Scores of the G sub-classifier came out to be 0.60, 0.61, 0.60 respectively. Similarly, the precision, recall and F1 score of the P sub-classifier and the I sub-classifier came out to be 0.65, 0.60, 0.61 and 0.59, 0.59, 0.59 respectively. We tried using BERT for subclassification, but the accuracy turned out to be 37%. The reason being a lesser number of annotated tweets for each subcategory.

Table 5: Confusion Matrix G Sub-Classifier

| **Actual / Predicted** | **G** | **P** | **I** |
|---|---|---|---|
| **G** | 5 | 1 | 1 |
| **P** | 2 | 10 | 2 |
| **I** | 1 | 2 | 2 |

Table 6: Confusion Matrix P Sub-Classifier

| **Actual / Predicted** | **G** | **P** | **I** |
|---|---|---|---|
| **G** | 10 | 4 | 1 |
| **P** | 6 | 9 | 0 |
| **I** | 1 | 5 | 7 |

Table 7: Confusion Matrix I Sub-Classifier

| **Actual / Predicted** | **G** | **P** | **I** |
|---|---|---|---|
| **G** | 8 | 4 | 2 |
| **P** | 4 | 9 | 2 |
| **I** | 2 | 2 | 6 |

All user tweets were classified using the manually labeled tweets as training data, and then the tweet dump corresponding to each happiness state was analyzed through open coding qualitative clustering. The main open coding categories to which tweets belong, corresponding to each happiness state, are listed in Table 8.

Table 8: Open Coding Categorization of 9 happiness states

| | | |
|---|---|---|
| **GG**: helping others, self improvement, gratitude, tolerance, inclination to learn from scriptures, resilience, emphathetic, encouraging | **GP**: focus on their priorities, self preferences, work focused, enjoyment along with others, regulated | **GI**: show & movies, Anxiety or sadness |
| **PG**: concern for others, appreciative, work oriented (tech), thoughtful, some regulation, sense of togetherness | **PP**: frustration, attachment, games & sports | **PI**: slangs and abuses, criticism movie e.g.crime, envy, depression & frustation |
| **IG**: pursuing hobbies and interests, struggling to cope up, wishing good for others | **IP**: escaping a negative situation, fighting against oppression, longing & craving, music & shows, food and drinks | **II**: unhappy with oneself, accepting and attributing depression for everything, movies & murder mysteries, music, miserable, brooding how people reject them |

## 6 Conclusion

In this paper, we performed causal inference on tweets of 54,066 users (after filtration) to find out activities which lead to transitions from G to P, G to I and P to I states. It was found that:

1. Excessive focus on Work, Money & Economy, Technology & Digital Life, food & drink, politics & society, physical environment, sports & music & public events; leads one to GP transition
2. Excessive focus on personal or interpersonal struggles expressed in emotions, personal entertainment (movie, dream etc.), and mental health issues leads one to GI transition.
3. Activities leading to PI transition are similar to those of GI with addition of Food & Drink, more individual relationships

Then we incorporated motivation/attitude/intent in our 3 stage happiness model expanding it to a 9 stage model with states GG, GP, GI, PG, PP, PI, IG, IP, and II states. With two stage XgBoost classification, each user tweet was categorized into one of the 9 states. Analysis of the classified tweets revealed:

1. Prominence of work and self as preference is characteristic of GP state
2. Entertainment (movies, shows), anxiety & sadness is characteristic of GI state
3. Slangs and abuses, criticism, movie e.g.crime, envy, depression & frustation are characteristic of PI state

The results from causal analysis and 9 stage happiness modelling are consistent. One can be careful in choosing which activities to zoom as the acts enlisted above makes one transition towards unhealthy and inauspicious directions.
To regulate the G to P/I or P to I transitions some suggested measures can be:
G to P

1. Encouraging internal value assessments over external validation (like performance) in workplace.
2. Limiting overexposure to trending public content by personalizing feed diversity and promoting deeper, self-reflective content to counteract public-performance loops.
3. Introducing value based education

G to I

1. Early detection systems like AI mood trackers can be created and low-threshold support (chatbots, peer responders) can be provided.
2. Media houses can be encouraged to rate and flag emotionally intense or destabilizing content (similar to nutrition labels).
3. Coping skills through story-based workshops (e.g., narrative therapy, journaling, expressive arts) can be incorporated in education training.

P to I

1. Education curriculum can be so designed to provide frameworks for healthy boundaries, emotional communication, and relationship repair.
2. Emotional intensity in interactions can be detected and reflection prompts, pause nudges, or "reach out" suggestions can be offered by workplace or social platforms.

In future work, we intend to work on time variation analysis of the 9 happiness states. We intend to enhance the manual annotations to incorporate BERT based models for sub-classification. Also, make use of data augmentation techniques to enhance the gold standard data.
**Reproducibility.** The code is available at
https://github.com/mayankbhasin/transitions_happiness_states

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