

# Mental Health Coping Stories on Social Media: A Causal-Inference Study of Papageno Effect

Yunhao Yuan  
yunhao.yuan@aalto.fi  
Aalto University  
Espoo, Finland

Koustuv Saha  
koustuv.saha@gmail.com  
Microsoft Research  
Montreal, Canada

Barbara Keller  
barbara.keller@aalto.fi  
Aalto University  
Espoo, Finland

Erkki Tapio Isometsä  
erkki.isometsa@hus.fi  
University of Helsinki  
Espoo, Finland

Talayeh Aledavood  
talayeh.aledavood@aalto.fi  
Aalto University  
Espoo, Finland

## ABSTRACT

The Papageno effect concerns how media can play a positive role in preventing and mitigating suicidal ideation and behaviors. With the increasing ubiquity and widespread use of social media, individuals often express and share lived experiences and struggles with mental health. However, there is a gap in our understanding about the existence and effectiveness of the Papageno effect in social media, which we study in this paper. In particular, we adopt a causal-inference framework to examine the impact of exposure to mental health coping stories on individuals on Twitter. We obtain a Twitter dataset with ~2M posts by ~10K individuals. We consider engaging with coping stories as the Treatment intervention, and adopt a stratified propensity score approach to find matched cohorts of Treatment and Control individuals. We measure the psychosocial shifts in affective, behavioral, and cognitive outcomes in longitudinal Twitter data before and after engaging with the coping stories. Our findings reveal that, engaging with coping stories leads to decreased stress and depression, and improved expressive writing, diversity, and interactivity. Our work discusses the practical and platform design implications in supporting mental wellbeing.

## CCS CONCEPTS

• **Human-centered computing** → *Empirical studies in collaborative and social computing; Social media*; • **Applied computing** → *Psychology*.

## KEYWORDS

social media, mental health, suicidal ideation, natural language, causal inference, Papageno effect

## ACM Reference Format:

Yunhao Yuan, Koustuv Saha, Barbara Keller, Erkki Tapio Isometsä, and Talayeh Aledavood. 2023. Mental Health Coping Stories on Social Media: A Causal-Inference Study of Papageno Effect. In *Proceedings of the ACM Web*

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).  
WWW '23, May 1–5, 2023, Austin, TX, USA  
© 2023 Copyright held by the owner/author(s).  
ACM ISBN 978-1-4503-9416-1/23/04.  
<https://doi.org/10.1145/3543507.3583350>

Conference 2023 (WWW '23), May 1–5, 2023, Austin, TX, USA. ACM, New York, NY, USA, 9 pages. <https://doi.org/10.1145/3543507.3583350>

## 1 INTRODUCTION

According to a report from the World Health Organization [58], globally, approximately 700,000 people fall victim to suicide each year. Suicide attempts and particularly committed suicides cause severe and tragic consequences among relatives and friends of the victims, as well as significant economic problems for society. Consequently, suicide has become a crucial global public health problem, and the World Health Organization has called for urgent action to reduce the suicide mortality rate.

While suicide is a combined outcome of multiple, interrelated factors, ranging from mental health issues to social factors, media can play an important role either in a harmful or beneficial direction. A considerable amount of literature [16, 25, 49] has studied and re-confirmed the harmful effect of media, dubbed the “Werther effect” [38], describing a spike in suicides after a heavily publicized suicide. However, there is much less research about the beneficial effects of media, referred to as the “Papageno effect”, describing a decrease in suicides after reporting alternatives to suicide. Niederkrotenthaler et al. explored the possible protective effect of media reporting about suicide [34]. This study finds a decrease in suicides, if reports of suicide related content portray ways of overcoming suicidal ideation without narrating suicidal behaviors. This work provides important insights into the potential benefits of media that reports suicide related content with a focus on hope and recovery. Following this work, other studies provide evidence of the Papageno effect from fictional films [53], suicide-educational websites [54], and newspaper articles [1]. Given the prevalence and importance of social media, understanding more about the Papageno effect on social media can play a crucial role in decreasing suicide rates.

Studies of the Papageno effect commonly rely on self-reports, surveys, and publicly reported suicide statistics and only cover a small, selected group of people. People with suicidal ideation can face negative attitudes and stigmatization, which prevents many of them from seeking help [40]. Additionally, the sensitive nature of suicide makes it challenging to collect data at scale on individuals who have suicidal ideations and conduct continuous long-term follow-up studies.

The emergence of social media platforms, such as Twitter, Reddit, and TikTok, provides venues for people to not only connect

with others, but also to express and share different aspects and life events of their personal lives [43]. Social media platforms provide a non-intrusive means to collect people’s naturalistic data at scale. Research has leveraged social media data from different social media platforms to explore psychological and health issues using data from various domains such as drug misuse [18], minority stress [59], and mental health [9, 48]. Social media platforms provide timely and relevant information on examining risk attributes longitudinally. The anonymous features of social media may reduce the biases found in research based on surveys and self-reported data. Consequently, social media data provide an unparalleled opportunity to study the Papageno effect in a broader population and its evolution over time.

In this paper, we leverage public data from Twitter, a popular social media site. We analyze longitudinal posts from Twitter users who reply to posts containing stories about coping with suicidal ideation. We examine psychosocial changes in affective, behavioral, and cognitive outcomes related to suicidal ideation. Specifically, we target the research questions of, *whether the Papageno effect exists on Twitter and how we can quantify psychosocial changes of Twitter users before and after engaging with Twitter posts containing mental health coping stories.*

To achieve the research goals, we collect 13,022 Twitter posts containing keyword phrases, which might indicate coping stories. We utilize a machine learning classifier from a previous study [29] to automatically annotate the dataset and 3,077 Twitter posts are labeled as coping stories, which might result in the Papageno effect. Among them, we manually verify the accuracy of the classifier on a sampled coping story dataset. We collect data from two populations on Twitter: 787K posts from 2,468 individuals who reply to Twitter posts containing coping stories and 1.4M posts from 8,465 individuals in a control group. After applying stratified propensity score matching, we aggregate psychosocial outcomes as affective, behavioral, and cognitive outcomes and identify these with high significant effects. We observe that engaging with coping story posts on Twitter is linked to lower stress and depression, and higher expressive writing, diversity, and interactivity.

**Privacy and Ethics.** Although we use public accessible data from Twitter, we are committed to protect the privacy of the data owners. We remove any information related to personal identity and paraphrase all quotations in this paper to avoid traceability. Given the sensitive nature of the topic of suicide and to avoid potential misuse, we adhere to Twitter data sharing standards and will only share the Twitter post IDs to other researchers. One of the authors is a certified psychiatrist. This helps us better understand our findings.

## 2 RELATED WORK

### 2.1 Media Effects on Suicidal Ideation

The question of how media reports about suicide influence subsequent suicides has received considerable attention [31]. For quite some time, studies focus on the negative impact of media portrayals on suicide and find a positive correlation between media coverage of suicidal behavior and suicidality [14]. These studies spark a debate about the possible preventive impact of media on suicide rates.

While one body of research highlights that increasing public understanding of mental health therapy may prevent suicide attempts [5], others suggest that negative media coverage of suicides, such as the suicide victim’s non-attractive features or the circumstances of the suicidal act, prevents imitative suicidal attempts [39]. Niederkrotenthaler et al. discover that reports of people who considered suicide but afterward dealt with their problems constructively are linked to a short-term reduction in suicide rates in 2010. This preventive effect is coined the “Papageno effect”. Inspired by the Papageno effect, Till et al. [52] conduct a randomized controlled trial to explore the beneficial impact of educative newspapers featuring suicide researchers in 2018. They observe similar suicide-protective effects on both readers with, as well as readers without personal experience of suicide ideation. To further test the Papageno effect, Niederkrotenthaler et al. conduct meta-analysis research and provide new evidence supporting the beneficial effect of media on individuals with suicidal ideation if the media narratives focus on hope and recovery from suicidal crises [33].

So far, however, the Papageno effect on social media is understudied. Our work attempts to examine the psychosocial impacts of the Papageno effect on Twitter. We gather longitudinal social media data and compare multiple psychosocial outcomes of individuals engaging with coping story posts with a matched Control group.

### 2.2 Mental Health and Psycholinguistics

Although suicide is not an inevitable consequence of any psychiatric condition, research suggests a link between mental health and suicidal behaviors. According to a psychiatric autopsy study [6], more than 90% of people who die by suicide suffer a mental disorder previous to their death. Patients who report anhedonia and sleeplessness with major anxiety symptoms, alcohol abuse, or emotional problems have the highest short-term risk for suicide [24].

Studying suicidal ideation attracts researchers from different fields. Research suggests that psychological linguistic metrics may be used to characterize people with suicidal ideation [2]. Stirman and Pennebaker compare the linguistic expression of poets between a small sample of suicidal and non-suicidal individuals, using a computerized text-analysis program called Linguistic Inquiry and Word Count (LIWC) [36]. The authors observed more self-references through first-person singular pronouns, more words related to death, and fewer social references in the poets written by those who did die by suicide [50]. Following that, other studies have used LIWC and similar language analysis techniques to analyze lexical and linguistic features in the text of suicidal individuals from different cultural backgrounds [17, 20, 27]. For example, Litvinova et al. [28] use the Russian edition of the LIWC lexicon to analyze the text from blog posts and find that texts written by confirmed suicidal individuals, containing more negation words, fewer social and perception-related words, fewer positive emotion words than texts from a control group.

All together, these studies provide a core understanding of leveraging mental and psycholinguistic cues for understanding the Papageno effect on social media. Based on the public content shared on the social media platform, we focus on inferring psychosocial outcomes from the perspectives of affect, behavior, and cognition.

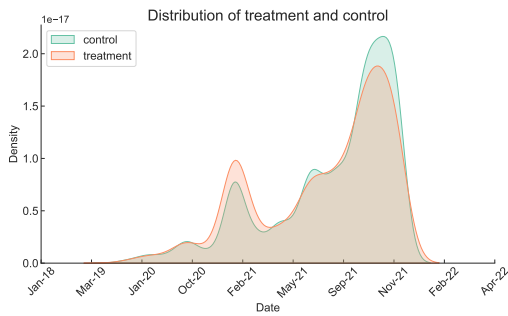


Figure 1: Treatment and Control (placebo) dates distribution.

### 2.3 Social Media and Mental Health Research

The emergence of social media provides a new powerful “lens” to give insights into mental health and suicidal ideation. Prior research uses social media posts to understand more about major depressive disorders [10], risk suicide behavior [9], and drug use [45].

Relatedly, Kumar et al. compare the posting activity and content following celebrity suicides to find a rise in posting frequency and increased suicidal ideation [25]. Another work reveals the importance of linguistic features to predict users who move from mental health discourse to suicidal ideation [12]. Based on Reddit postings, the authors develop a propensity score matching to investigate how individuals may discuss their suicidal ideation while controlling for the previous use of linguistic features of mental health. Following this work, De Choudhury and Kiciman [11] apply a similar matching framework to study the effect of social support on suicidal ideation risk. In another work, Saha and Sharma conduct a causal-inference examination of what factors contribute to improved mental wellbeing in online mental health communities (particularly TalkLife) [44].

Our work draws motivation from the above body of work in examining the prevalence of the Papageno effect following being exposed to coping story posts on suicidal ideation on social media. Our work adopts the natural language techniques and causal inference analyses to provide a computational framework of measuring this effect and reveals important insights about how people show changes in social media behaviors after engaging with coping story posts.

## 3 DATA

Due to the absence of publicly available datasets of coping story posts in social media, we utilize Twitter timeline data of individuals who reply to coping story Twitter posts. The steps of data collection include: 1) collecting Twitter posts, which might describe coping stories; 2) applying coping story classifier from [29] and manually verifying the results; 3) collecting timeline data of individuals commenting on the so found coping story posts; 4) building a control dataset from randomly sampled, comparable, individuals.

### 3.1 Compiling the Coping Story Posts Dataset

The first step is to retrieve Twitter posts that may contain coping stories. This work uses the Twitter Application Programming Interface (API) to collect Twitter posts posted between 1 January 2018

Table 1: Paraphrased example Twitter posts labeled with coping story or non-coping story and Twitter posts responding to coping story posts.

#### Coping Story Posts

“I’m posting this because I’ve had suicide ideas passively for a long time. I finally realized I was suicidal three years ago. I believed that the desire to be better off dead was common. It is NOT the norm. If you have such ideas, you should seek professional assistance.”

“When I was a patient in the psychiatric hospital, they had to remove my shoelaces to prevent me from self-injury. Today marks one month without suicide ideation. My life has improved after receiving therapy from all of my physicians. Cheers to the continuation of living in the present!”

#### Non-Coping Story Posts

“Even more terrible than my thoughts of death are my suicide ideas. People told me when I was 10 that it would get better, but it hasn’t, and I want to die yet nothing works. It’s so unfair that no matter how many times I try, I always fail. I’m sorry if this is frustrating; I just feel so alone.”

“But I wanted to kill myself again this weekend. I’ve never been happier. But every day is so full of grief for the body I don’t have and will never be capable of having.”

#### Twitter Posts Responding to Coping Story Posts

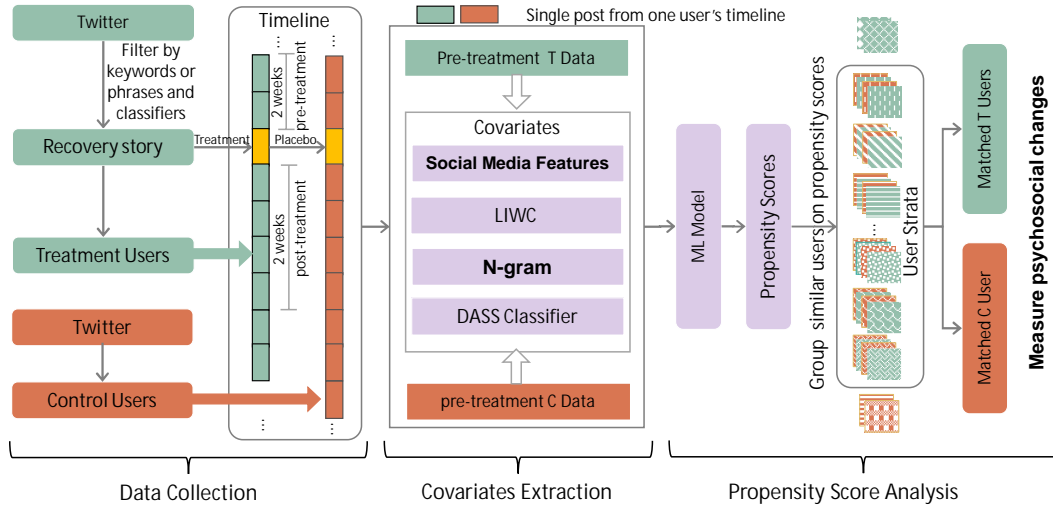
“Dear friend, I’m happy that things didn’t turn out the way you had hoped. I wouldn’t want the past few of years to have been any other way because they have been such an adventure. To where we all go in the future is something I am looking forward to see.”

“I’m glad to hear that you’re doing well. It’s good to know that you have support from close friends and family because I am aware of how challenging it may be to handle some circumstances.”

and 1 March 2022. The collected Twitter posts contain at least one term related to suicide attempts, including “suicidal thoughts,” “kill myself,” “suicidal ideation,” and “end my life,” and contain at least one of the terms indicating successful coping, including “happier,” “better,” and “recover”. After collecting 13,022 Twitter posts, we apply the coping story classifier to annotate each Twitter post as a coping story or a non-coping story. We find 3,077 Twitter posts are annotated as coping story posts. Among them, 709 Twitter posts labeled as coping story posts have at least one reply below them.

**3.1.1 Annotating Coping Story Posts.** We use a multi-label classifier provided by Metzler et al. to annotate coping story posts in our dataset. It categorizes Twitter posts into the following six categories [29]:

- (1) Personal experiences of coping (coping story): Personal experiences about suicide that express a feeling of hope, healing, methods of coping, or reference alternative options to suicide. The tone could be positive or neutral. Previous studies suggest that such narratives may have a Papageno effect.
- (2) Personal experiences of suicidal ideation and attempts: Personal stories about suicide that lack a sense of coping or hope.
- (3) Suicide cases: Reports of suicides that have been carried out or prevented



**Figure 2: Schematic diagram of propensity score matching between Treatment individuals and Control individuals.**

- (4) Awareness: Twitter posts raising awareness about suicide, emphasizing high rates or links to problems such as such as bullying, racism, depression, or veteran status.
- (5) Prevention: Twitter posts that provide information on solutions or initiatives aimed at addressing the problem of suicide, including prevention at both individual and public health levels.
- (6) Twitter posts that do not fall under any of the above categories.

As the aim of this step is to find individuals who comment on coping story posts, we subsequently focus on Twitter posts labeled as a coping story post. In order to verify the ability of the classifier to find Twitter posts that contain actual coping stories, we manually check Twitter posts that are labeled as coping story posts by the classifier.

**3.1.2 Annotation Task.** We randomly sample 400 Twitter posts out of 709 Twitter posts labeled as coping stories that have at least one reply below them. Using the codebook from [29], one author independently annotates 400 Twitter posts. If there are any posts that they are unsure about, the author discusses the posts with other authors and together they reach an agreement on how to code them. After finishing the annotation, another author randomly selects 50 posts out of 400 posts to verify the annotation result. We use Cohen’s kappa to validate our annotation process. This results in Cohen’s  $k$  of 0.81 with an agreement of 92.8%, which indicates substantial agreement [26]. Out of the 400 posts labeled coping story by the classifier, we find 347 posts are correct predictions, indicating 86.7% accuracy of the classifier to identify copy story posts.

### 3.2 Compiling the Treatment Dataset

For the Twitter posts annotated as coping story posts, we assume that the individuals who reply to the Twitter posts might have been impacted by the coping story. For our coping story dataset, we identify 2470 unique individuals who replied to at least one

coping story. We collect Twitter metadata, including the number of posts, likes, followers, followees, and the account creation time. To mitigate the confounding effects of engaging with multiple coping story posts, we remove 2 individuals who reply to multiple coping story posts. For the remaining 2468 individuals, we collect their timeline data two weeks before their reply on the coping story and two weeks after. In the end, the target dataset contains 2468 individuals with a total of 787K Twitter posts.

### 3.3 Compiling the Control Dataset

As we seek to isolate the effect of the coping story on individuals, we build a Control dataset of individuals who do not reply to coping story posts during the investigated period. To do so, a Control dataset is built with individuals who have similar attributes to the treatment individuals prior to their engagement with a coping story. To find such control individuals, we use keywords, including “life”, “job”, “music”, and “movie” to search for individuals on Twitter. For each keyword, we collect 4000 individuals and the timeline of their Twitter posts. For each individual in the Control dataset, We assign a placebo date from the non-parametric distribution of treatment date in the Treatment dataset to any day the Control individual replies to other Twitter posts to reduce any temporal confounds. We utilize Kolmogorov-Smirnov (KS) test to measure the similarity in the two distributions (Figure 1). The KS test yields a low statistic of 0.05, suggesting that the probability distributions of treatment and placebo dates are similar. In the end, we collect timeline data two weeks before the placebo date and two weeks after of 8465 individuals to build the *control* dataset.

## 4 METHODS

### 4.1 Study Design and Rationale

We adopt a causal inference framework [21] to isolate the Papageno effect. The schematic diagram of our approach is shown in Figure 2. Our approach first matches individuals of the Control group with

individuals of the Treatment group<sup>1</sup> based on pre-Treatment behavioral attributes. For this, we train a machine learning classifier to estimate the likelihood of an individual being assigned to either the Treatment or Control group (i.e., *propensity*) based on covariates and perform matching across groups using estimated propensity scores. Within matched groups of Control and Treatment groups, we analyze the following psychosocial outcomes between matched Control groups and Treatment groups. In sum, our approach ensures that members of the Treatment group and Control group who are being compared have similar behavior prior to replying to coping story posts. This gives us the means to analyze the differences in psychosocial outcomes between the matched Treatment individuals and the members of the Control group.

## 4.2 Measuring Psychosocial Outcomes

To examine the psychosocial effects of engaging with coping story posts on social media, we measure three psychosocial outcomes drawing from psychiatry and psychology literature: affective, behavioral, and cognitive outcomes [4]. We operationalize these measures drawing on prior research in social media and mental health [44, 47].

**Affective Outcomes** Affect is defined as any experience of feeling or emotion [55]. As individuals use emotive, relativistic language in their self-motivated online texts, language is an effective way to infer affective psychosocial wellbeing. To estimate affective outcomes, we use the following metrics:

*Affective Words.* We employ the well-validated psycholinguistic lexicon, Linguistic Inquiry and Word Count (LIWC) [35] to obtain normalized occurrences of words in affective categories per individual. The selection of these measures is inspired by studies like [10, 15, 47], where therapeutic symptoms are associated with self-initiated and expressive writing [7, 8].

*Symptomatic Mental Health Expressions.* Prior research notes the comorbidity of multiple mental health conditions [41], and we operationalize the language indicative of different mental health symptomatic expressions of depression, anxiety, stress, and suicidal ideation [45]. To identify mental health symptomatic expressions in social media language, Saha et al. [45] develop multiple binary machine learning classifiers based on transfer learning methodologies. These classifiers are  $n$ -gram-based ( $n=1,2,3$ ) binary support vector machine (SVM) models, and are trained using appropriate Reddit communities (*r/depression* for depression, *r/anxiety* for anxiety, *r/stress* for stress, and *r/SuicideWatch* for suicidal ideation). People in these communities post about mental health symptoms to receive feedback and to support others. The posts in these subreddits are used as training data to identify language used in connection with mental health. The training data for texts not related to mental health originates from non-mental-health-related content on Reddit. These classifiers perform at a high accuracy of approximately 0.90 on average on held-out test data [45], and have also been used in other research [44, 46]. We use these classifiers to measure the aggregated proportion of expressing mental health concerns per

individual. A lower quantity of posts on mental health symptomatic expressions indicates better psychosocial wellbeing.

**Behavioral Outcomes.** Literature in psychology defines behavioral psychological well-being as including three factors: individual's overt actions, behavioral intentions, and verbal statement regarding behavior [4]. Previous studies quantify behavioral psychological wellbeing by measuring the shifts in social functioning and interests [19, 47]. Our work operationalizes the following measures to obtain behavioral outcomes.

*Activity.* We investigate if engaging with coping story posts promotes individuals to be more active on Twitter. Higher activity likely indicates increased extroversion, and is associated with therapeutic benefits [15, 47]. To quantify activity on Twitter, we calculate the average number of Twitter posts per day for every individual.

*Interactivity.* Interactivity is another indicator of an individual showing therapeutic effects [44, 47]. We measure participation in discussions on Twitter as interactivity, indicating social engagement. The metric used is the proportion of replies (to other individuals' posts) per original Twitter post.

*Topic Diversity.* To measure the diversity of topics discussed by an individual, we apply a language model on the posted texts. We capture language semantics by adopting a word embedding model [30], which represents words in vectors in latent semantic dimensions. In particular, we use 300-dimensional word embeddings pre-trained on Google News. Then, for each post from the Treatment and Control datasets, we calculate the average cosine distance from the centroid of the corresponding corpus. Higher the average the distance from the centroid, greater is the topical diversity [57].

**Cognitive Outcomes.** The cognitive component of psychosocial health encompasses beliefs, knowledge structures, perceptual responses, and thoughts [4]. We adopt the following measures to quantify an individual's cognitive behaviors.

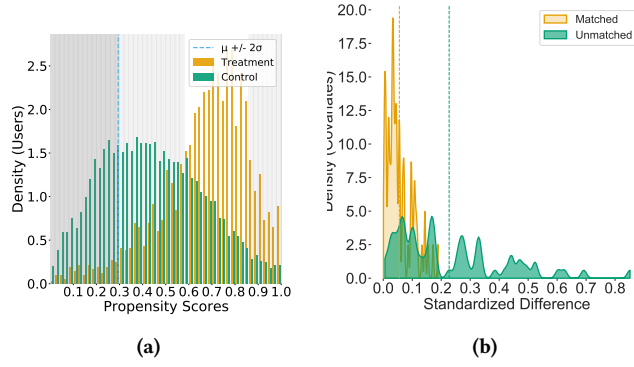
*Readability.* Readability measures the complexity of a given text. We employ the Coleman-Liau Index (CLI) to assess the readability per individual. CLI is calculated as,  $CLI = 0.0588 * L - 0.296 * S - 15.8$ , where  $L$  is the average number of letters per 100 words and  $S$  is the average number of sentences per 100 words. Previous research shows a link between measures of language complexity and long-term improvements in psychosocial wellbeing [15].

*Complexity and Repeatability.* Complexity and Repeatability are syntactic measurements that reflect an individual's cognitive state in terms of planning, execution, and memory [15]. We measure repeatability as the normalized count of non-unique words and complexity as the average number of words per sentence. Psychosocial wellbeing positively correlates with language complexity, and negatively with repeatability [15, 47].

*Psycholinguistic Keywords.* We adopt the LIWC lexicon to analyze the proportion of keywords related to cognition, perception, social context, and linguistic style categories. We consider the following five aggregated categories: (1) Cognition & Perception (cause, certain, cognitive, inhibition, discrepancies, tentativeness, perception, see, hear, feel, insight) (2) Social Context (biological processes, achievement, body, family, friends, health, home, humans, money, religion, social, work) (3) Lexical Density & Awareness (adverbs,

<sup>1</sup>Treatment: Conventionally, "Treatment" refers to being given Treatment or intervention. We use the term "Treatment" in accordance with the causal inference terminology to differentiate individuals replying to coping story posts and the individuals not replying to coping story posts.





**Figure 3: (a) Propensity score distribution (shaded region are the dropped strata), (b) Quality of matching.**

article, verbs, auxiliary verbs, conjunctions, inclusive, exclusive, preposition, negation, quantifier, relative) (4) Interpersonal Focus (1st personal pronouns, 2nd personal pronouns, Impersonal pronouns) (5) Temporal References (future, past, present). Prior research highlight the association between these lexicons and cognition [37]. An increased use of these lexicons is related to better psychological conditions [7, 8].

### 4.3 Matching

**4.3.1 Matching Covariates.** Our goal is to measure the psychosocial outcomes of engaging with a coping story post. Matching is an efficient strategy in Case-Controlled studies to estimate causal effects and minimize the possible occurrence of selection biases. In our case, we build several covariates from the Treatment and Control datasets to control for similar pre-Treatment behavior on social media. The first set of covariates comprises Twitter individuals' social media features (the number of posts, likes, followers, followees, and posting frequency). The second set contains the distribution of word usage in their Twitter timelines. We extract the top 100 unigrams as the second covariates set. The third set includes the psycholinguistic features in their timeline data by measuring the word distribution in the LIWC lexicon. The last set of covariates controls for the average usage of posts related to symptomatic mental health expressions, including depression, anxiety, stress, and suicidal ideation.

**4.3.2 Propensity Score Analysis.** To ensure to have comparable individuals in our Treatment dataset and the Control dataset, matching is employed to pair Treatment individuals and Control individuals, whose covariates are similar to each other. A logistic regression classifier is implement to predict the likelihood of an individual belonging to either the Treatment group or Control group based on their covariates. We divide the propensity score distribution into 50 strata with equal width. The individuals with similar propensity scores are grouped into the same stratum [22]. This helps us to evaluate possible psychosocial outcomes within each stratum, where the Control group individuals are matched to the Treatment individuals based on the pre-Treatment behavioral traits. We remove the individuals with propensity scores falling outside two standard deviations from the mean (Figure 3a ). We drop the strata failing

to satisfy the minimum sample size within each stratum based on previous causal inference research [13]. By ensuring that there are at least 50 individuals per group in each stratum, this approach results in 14 strata, containing 1,245 Treatment and 1,087 Control individuals.

**4.3.3 Quality of Matching.** To determine whether individuals in the Treatment group and Control group are statistically comparable, we measure the balance of the covariates. We conduct this comparison by calculating the standardized mean differences (SMD) between the two groups in all 14 valid strata [22, 45]. SMD is the difference in the mean covariate values between the two matched groups, divided by the pooled standard deviation. The two groups can be assumed to be balanced if the SMD of all covariates is lower than 0.2 [22, 42, 51]. For the unmatched dataset, the maximum SMD is 0.85, and the mean SMD is 0.22, whereas in our matched dataset, the maximum SMD is 0.19 and the mean SMD is 0.06 (Figure 3b). Therefore, this satisfies the threshold of  $SMD < 0.2$ , suggesting that our matching yields balanced Treatment and Control datasets.

**4.3.4 Estimating the Average Treatment Effects.** To estimate the effect of engaging with coping story posts, we compute the relative Treatment effect (RTE) for each outcome. For this, we calculate the ratio of likelihood of an outcome measure in the Treatment group to that in the Control group per stratum. Using the number of Treatment individuals in each stratum as a weight, we obtain the weighted average RTE per outcome. The outcome is interpreted as an increase (greater than 1) or decrease (less than 1) of observable psychosocial outcomes after engaging with coping story posts compared to the Control group with similar pre-Treatment attributes.

## 5 RESULTS

In this section, we present the shifts for each psychosocial outcome across the matched Treatment and Control individuals in the corresponding datasets. We calculate the effect size (Cohen's  $d$ ), and measure statistical significance in differences using an independent sample  $t$ -test. Figure 4 shows the distribution of RTE per stratum across different psychosocial outcomes. Table 2 summarizes these differences.

**Affective Outcomes.** *Affect.* In Table 2, we observe that individuals in the Treatment group use more affective words than the matched Control individuals after engaging with coping story posts. The average number of affective words used by Treatment individuals is 11% higher than among Control individuals. The effect size (Cohen's  $d=0.20$ ) suggests small differences between the two distributions and the  $t$ -test indicates statistical significance ( $t=2.19, p<0.05$ ). This observation affirms that individuals use more affective words after engaging with coping story posts.

**Symptomatic Mental Health Expressions.** We find that engaging with coping story posts is associated with decreases in the use of symptomatic stress and depression expressions. This is revealed by lower average percentages of symptomatic stress and depression Twitter posts from individuals in the Treatment group reflecting stress ( $t=-3.96, p<0.001$ ) and depression ( $t=-2.84, p<0.01$ ). In contrast, we find no significant differences in our measures of anxiety and suicidal ideation after individuals engage with coping story posts between the two corresponding groups. This illustrates that engaging with



**Figure 4: RTE per propensity stratum per outcome. The pink color indicates RTE greater than 1, while the green color suggests RTE less than 1.**

**Table 2: Summary of psychosocial differences across all the outcomes between Treatment and Control individuals. We report mean psychosocial outcomes across all matched individuals, effect size (Cohen’s  $d$ ), independent sample  $t$ -statistic. The  $p$ -values from LIWC categories are adjusted using non-negative two stage FDR correction ( $*p < 0.05$ ,  $**p < 0.01$ ,  $***p < 0.001$ ).**

Categories	Tr.	Ct.	RTE	$d$	$t$ -test
<b>Affective Outcomes</b>					
LIWC: Affect	0.09	0.08	1.05	0.20	2.19*
Anxiety	0.05	0.04	1.08	0.17	-0.33
Depression	0.15	0.17	0.93	0.28	-2.84**
Stress	0.35	0.38	0.94	0.28	-3.96***
Suicidal Ideation	0.07	0.06	1.04	0.15	-0.41
<b>Behavioral Outcomes</b>					
Activity	4.33	4.19	1.10	0.16	0.40
Interactivity	8.89	2.78	3.34	0.34	4.17**
Topics Diversity	0.37	0.36	1.02	0.25	2.51*
<b>Cognitive Outcomes</b>					
Readability	12.33	11.52	0.95	0.18	-2.16*
Complexity	9.26	9.52	0.99	0.19	-1.42
Repeatability	0.51	0.45	1.11	0.30	5.09***
LIWC: Cognition & Perception	0.27	0.27	1.02	0.17	1.12
LIWC: Social Context	0.18	0.17	1.01	0.08	0.55
LIWC: Lexical Density & Awareness	0.60	0.61	0.99	0.15	-1.23
LIWC: Interpersonal Focus	0.12	0.11	1.08	0.26	2.77*
LIWC: Temporal Reference	0.10	0.10	1.02	0.17	1.45

copying story posts does not increase the use of symptomatic anxiety and suicidal ideation expressions. These observations are consistent with prior research which indicates that media featuring individuals coping with depression and suicidal ideation reduces depression and shows no effect on suicidal ideation [32].

**Behavioral Outcomes.** For the second set of outcomes, we find no significant difference in activity after engaging with coping story

posts. We find that the average interactivity of the Treatment users is higher than the Control. Both effect size (Cohen’s  $d=0.34$ ) and independent  $t$ -test indicate statistical significance ( $t=4.17$ ,  $p<0.01$ ). This might suggest that engaging with coping story posts likely promotes an individual’s participation in online discussions. For topical diversity, we measure the diversity of expressed topics in posts after engaging with coping story posts; the effect size informs small differences between Treatment and Control distributions of topical diversity, and the  $t$ -test affirms statistical significance ( $t=2.51$ ,  $p<0.05$ ). This indicates individuals in Treatment group discuss a broader range of topics after engaging with coping story posts, suggesting higher psychological wellbeing.

**Cognitive outcomes.** To examine if engaging with coping story posts leads to shifts in cognition, we measure the differences in readability, complexity, repeatability, and psycholinguistic features. Among these, we find no significant differences in complexity, cognition & perception, lexical density & awareness, and temporal reference. However, we observe a significant difference in interpersonal focus ( $t=2.77$ ,  $p<0.05$ ). The changes in the usage of pronouns might suggest a shift in how individuals see themselves in relation to others. Although independent sample  $t$  indicates a significant difference in readability ( $t=-2.17$ ,  $p<0.05$ ), the result of cohen’s  $d$  shows no difference between the two distributions. One unanticipated finding is the Treatment individuals show higher repeatability compared to Control individual ( $t=5.09$ ,  $p<0.001$ ), which suggest lower psychosocial health.

## 6 CONCLUSION AND DISCUSSION

### 6.1 Summary of Findings

In this work, we develop a novel causal inference framework to verify and study the Papageno effect on social media. Using a Twitter dataset with  $\sim 2M$  posts by  $\sim 10K$  individuals, we observe statistically significant psychosocial (affective, behavioral, cognitive) shifts in individuals after engaging with coping story posts. In assessing these psychosocial effects, our causal framework controls behavioral and linguistic covariates across the Treatment and Control groups. We verify that engaging with coping story posts positively impacts individuals’ stress and depression, and improves expressive writing, topics diversity, and interactivity. Our results indicate that engaging with coping story posts on social media is associated with positive benefits for one’s psychosocial wellbeing.

### 6.2 Implications

While we do not directly measure shifts in suicidal ideation itself, our findings still provide evidence for the Papageno effect on social media. Our results suggest that engaging with posts describing personal stories featuring coping with suicidal ideation can bring positive impacts on psychosocial wellbeing. Our work provides a methodology to help measure the psychosocial outcomes of the Papageno effect on social media. By focusing on the psychosocial shifts of a large sample of individuals who engage with coping story posts, our work suggests a role for utilizing social media to access the prospective psychosocial outcomes of the Papageno effect.

Our work bears practical implications for preventing suicide. Online communities may develop strategies for the narratives about

sharing suicidal behaviors and ideation, allowing vulnerable members in the community more protected. Our work bears design implications for social media platforms in terms of how these platforms can encourage positive and thriving behavior, especially for those struggling with mental health concerns. Platforms such as Reddit, TalkLife, and 7Cups follow community-driven moderation strategies, and these platforms can include in their community norms what kinds of postings and support can help people draw therapeutic benefits. Social media platforms can show more posts with the Papageno effect when individuals search for suicidal information. These may be beneficial for individuals engaging with coping story posts and helpful for individuals with suicidal ideation to seek support and prevent tragic outcomes.

### 6.3 Limitations and Future Work

We acknowledge our study has several limitations, some of which point to intriguing future research directions. We do not account for passive engagement behaviors. For example, we do not know if an individual read a coping story and is affected by it if this individual does not reply to it. Another limitation is the time of our measurement. We only measure the averaged psychosocial outcomes within two weeks after an individual engaged with a coping story post. However, the psychosocial outcomes may vary over time and show fluctuating results [3]. Future work can explore psychosocial shifts in a fine-grained temporal manner.

Our study suffers from *selection biases*. We gather data from those who publicly reply to coping story posts on Twitter, which is likely to be influenced by self-selection bias. We can only collect data from individuals who are active on social media. This is especially true considering the stigma associated with people having suicidal ideation. In a similar manner, the scope of this study solely focuses on Twitter, which might result in incomplete or inaccurate perspectives. Therefore, our observations might not be generalized to other online communities on Twitter or beyond.

We acknowledge the concerns raised by King and Nielsen [23], and are aware of the limitations of the propensity score methods. We chose to use the well-established stratified propensity score method in our study [22, 44, 47, 56]—it offers a more robust approach to mitigate the confounds, by essentially balancing for the bias-variance trade-off. This method, therefore, addresses some of the biases and limitations inherent in propensity score methods [23]. It is important to note that, despite our best efforts to control for confounding variables, we cannot infer “*true causality*” in our study. As the outcomes might have been influenced by other online and offline factors, e.g., the individual’s suicidal behavior history, the length of a coping story post, and the length of the replies. Despite corroboration by a psychiatrist, we cannot be certain based on twitter posts that the individual is personally seriously considering suicide. Therefore the symptomatic variables and outcomes need additional clinical validation. Future work could combine social media data together with clinically validated data which could lead to more generalizable results on the Papageno effect and the role of social media.

## REFERENCES

[1] Florian Arendt, Benedikt Till, and Thomas Niederkrotenthaler. 2016. Effects of suicide awareness material on implicit suicide cognition: A laboratory experiment.

- Health Communication* 31, 6 (2016), 718–726.
- [2] Alan L Berman. 2005. FORENSIC PSYCHIATRY AND FORENSIC PSYCHOLOGY/ Psychological Autopsy. (2005).
- [3] Mehrab Bin Morshed, Koustuv Saha, Richard Li, Sidney K. D’Mello, Munmun De Choudhury, Gregory D. Abowd, and Thomas Plötz. 2019. Prediction of Mood Instability with Passive Sensing. *PACM IMWUT* (2019).
- [4] Steven J Breckler. 1984. Empirical validation of affect, behavior, and cognition as distinct components of attitude. *Journal of personality and social psychology* 47, 6 (1984), 1191.
- [5] Victoria Carmichael and Rob Whitley. 2019. Media coverage of Robin Williams’ suicide in the United States: A contributor to contagion? *PLoS one* 14, 5 (2019).
- [6] Jonathan TO Cavanagh, Alan J Carson, Michael Sharpe, and Stephen M Lawrie. 2003. Psychological autopsy studies of suicide: a systematic review. *Psychological medicine* 33, 3 (2003), 395–405.
- [7] Cindy Chung and James W Pennebaker. 2007. The psychological functions of function words. *Social communication* (2007), 343–359.
- [8] Michael A Cohn, Matthias R Mehl, and James W Pennebaker. 2004. Linguistic markers of psychological change surrounding September 11, 2001. *Psychological science* (2004).
- [9] Glen Coppersmith, Ryan Leary, Patrick Crutchley, and Alex Fine. 2018. Natural language processing of social media as screening for suicide risk. *Biomedical informatics insights* 10 (2018), 1178222618792860.
- [10] Munmun De Choudhury, Michael Gamon, Scott Counts, and Eric Horvitz. 2013. Predicting depression via social media. (2013).
- [11] Munmun De Choudhury and Emre Kiciman. 2017. The language of social support in social media and its effect on suicidal ideation risk. In *ICWSM*.
- [12] Munmun De Choudhury, Emre Kiciman, Mark Dredze, Glen Coppersmith, and Mrinal Kumar. 2016. Discovering shifts to suicidal ideation from mental health content in social media. (2016), 2098–2110.
- [13] Munmun De Choudhury, Sanket Sharma, and Emre Kiciman. 2016. Characterizing Dietary Choices, Nutrition, and Language in Food Deserts via Social Media. In *CSCW*.
- [14] Jan Domaradzki. 2021. The Werther effect, the Papageno effect or no effect? A literature review. *International journal of environmental research and public health* 18, 5 (2021), 2396.
- [15] Sindhu Kiranmai Ernala, Asra F Rizvi, Michael L Birnbaum, John M Kane, and Munmun De Choudhury. 2017. Linguistic markers indicating therapeutic outcomes of social media disclosures of schizophrenia. *PACM Human-Computer Interaction* CSCW (2017).
- [16] Robert A Fahey, Tetsuya Matsubayashi, and Michiko Ueda. 2018. Tracking the Werther Effect on social media: Emotional responses to prominent suicide deaths on twitter and subsequent increases in suicide. *Social Science & Medicine* 219 (2018), 19–29.
- [17] Mercedes Fernández-Cabana, Julio Jiménez-Félix, María Teresa Alves-Pérez, Raimundo Mateos, Ignacio Gómez-Reino Rodríguez, and Alejandro García-Caballero. 2015. Linguistic analysis of suicide notes in Spain. *The European Journal of Psychiatry* 29, 2 (2015), 145–155.
- [18] Sanjana Garg, Jordan Taylor, Mai El Sherief, Erin Kasson, Talayah Aledavood, Raven Riordan, Nina Kaiser, Patricia Cavazos-Rehg, and Munmun De Choudhury. 2021. Detecting risk level in individuals misusing fentanyl utilizing posts from an online community on Reddit. *Internet Interventions* 26 (2021), 100467.
- [19] Sharath Chandra Guntuku, J Russell Ramsay, Raina M Merchant, and Lyle H Ungar. 2019. Language of ADHD in adults on social media. *Journal of attention disorders* (2019).
- [20] Lori D Handelman and David Lester. 2007. The content of suicide notes from attempters and completers. *Crisis: The Journal of Crisis Intervention and Suicide Prevention* 28, 2 (2007), 102.
- [21] Guido W Imbens and Donald B Rubin. 2015. *Causal inference in statistics, social, and biomedical sciences*. Cambridge University Press.
- [22] Emre Kiciman, Scott Counts, and Melissa Gasser. 2018. Using longitudinal social media analysis to understand the effects of early college alcohol use. (2018).
- [23] Gary King and Richard Nielsen. 2019. Why propensity scores should not be used for matching. *Political analysis* 27, 4 (2019), 435–454.
- [24] Phillip M Kleespies and Elizabeth L Dettmer. 2000. An evidence-based approach to evaluating and managing suicidal emergencies. *Journal of Clinical Psychology* 56, 9 (2000), 1109–1130.
- [25] Mrinal Kumar, Mark Dredze, Glen Coppersmith, and Munmun De Choudhury. 2015. Detecting changes in suicide content manifested in social media following celebrity suicides. In *Proceedings of the 26th ACM conference on Hypertext & Social Media*. 85–94.
- [26] J Richard Landis and Gary G Koch. 1977. The measurement of observer agreement for categorical data. *biometrics* (1977), 159–174.
- [27] David Lester, Janet Haines, and Christopher L Williams. 2010. Content differences in suicide notes by sex, age, and method: A study of Australian suicide notes. *Psychological Reports* 106, 2 (2010), 475–476.
- [28] Tatiana A Litvinova, Pavel V Seredin, Olga A Litvinova, and Olga V Romanchenko. 2017. Identification of suicidal tendencies of individuals based on the quantitative analysis of their internet texts. *Computación y Sistemas* 21, 2 (2017), 243–252.



- [29] Hannah Metzler, Hubert Baginski, Thomas Niederkrotenthaler, and David Garcia. 2021. Detecting Potentially Harmful and Protective Suicide-related Content on Twitter: A Machine Learning Approach. *arXiv preprint arXiv:2112.04796* (2021).
- [30] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*. 3111–3119.
- [31] Thomas Niederkrotenthaler and Benedikt Till. 2019. Suicide and the media: From Werther to Papageno effects—A selective literature review. *Suicidologi* 24, 2 (2019).
- [32] Thomas Niederkrotenthaler and Benedikt Till. 2020. Effects of awareness material featuring individuals with experience of depression and suicidal thoughts on an audience with depressive symptoms: randomized controlled trial. *Journal of behavior therapy and experimental psychiatry* 66 (2020), 101515.
- [33] Thomas Niederkrotenthaler, Benedikt Till, Stefanie Kirchner, Mark Sinyor, Marlies Braun, Jane Pirkis, Ulrich S Tran, Martin Voracek, Florian Arendt, Maria Ftanou, et al. 2022. Effects of media stories of hope and recovery on suicidal ideation and help-seeking attitudes and intentions: systematic review and meta-analysis. *The Lancet Public Health* 7, 2 (2022), e156–e168.
- [34] Thomas Niederkrotenthaler, Martin Voracek, Arno Herberth, Benedikt Till, Markus Strauss, Elmar Etzersdorfer, Brigitte Eisenwort, and Gernot Sonneck. 2010. Role of media reports in completed and prevented suicide: Werther v. Papageno effects. *The British Journal of Psychiatry* 197, 3 (2010), 234–243.
- [35] James W Pennebaker and Cindy K Chung. 2007. Expressive writing, emotional upheavals, and health. *Handbook of health psychology* (2007), 263–284.
- [36] James W Pennebaker, Martha E Francis, and Roger J Booth. 2001. Linguistic inquiry and word count: LIWC 2001. *Mahway: Lawrence Erlbaum Associates* 71, 2001 (2001), 2001.
- [37] James W Pennebaker, Matthias R Mehl, and Kate G Niederhoffer. 2003. Psychological aspects of natural language use: Our words, our selves. *Annual review of psychology* 54, 1 (2003), 547–577.
- [38] David P Phillips. 1974. The influence of suggestion on suicide: Substantive and theoretical implications of the Werther effect. *American sociological review* (1974).
- [39] David P Phillips. 1978. Airplane accident fatalities increase just after newspaper stories about murder and suicide. *Science* 201, 4357 (1978), 748–750.
- [40] Alexandre Reynders, Ad JFM Kerkhof, Geert Molenberghs, and Chantal Van Audenhove. 2015. Help-seeking, stigma and attitudes of people with and without a suicidal past. A comparison between a low and a high suicide rate country. *Journal of Affective Disorders* 178 (2015), 5–11.
- [41] Joshua D Rosenblat, Ron Kakar, and Roger S McIntyre. 2016. The cognitive effects of antidepressants in major depressive disorder: a systematic review and meta-analysis of randomized clinical trials. *International Journal of Neuropsychopharmacology* 19, 2 (2016).
- [42] Koustuv Saha, Yozen Liu, Nicholas Vincent, Farhan Asif Chowdhury, Leonardo Neves, Neil Shah, and Maarten W Bos. 2021. AdverTiming Matters: Examining User Ad Consumption for Effective Ad Allocations on Social Media. In *Proc. CHI*.
- [43] Koustuv Saha, Jordyn Seybolt, Stephen M Mattingly, Talayah Aledavood, Chaitanya Konjeti, Gonzalo J Martinez, Ted Grover, Gloria Mark, and Munmun De Choudhury. 2021. What life events are disclosed on social media, how, when, and by whom?. In *Proceedings of the 2021 CHI conference on human factors in computing systems*. 1–22.
- [44] Koustuv Saha and Amit Sharma. 2020. Causal Factors of Effective Psychosocial Outcomes in Online Mental Health Communities. In *ICWSM*.
- [45] Koustuv Saha, Benjamin Sugar, John Torous, Bruno Abrahao, Emre Kiciman, and Munmun De Choudhury. 2019. A social media study on the effects of psychiatric medication use. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 13. 440–451.
- [46] Koustuv Saha, John Torous, Eric D Caine, Munmun De Choudhury, et al. 2020. Psychosocial effects of the COVID-19 pandemic: large-scale quasi-experimental study on social media. *Journal of medical internet research* 22, 11 (2020), e22600.
- [47] Koustuv Saha, Ingmar Weber, and Munmun De Choudhury. 2018. A Social Media Based Examination of the Effects of Counseling Recommendations After Student Deaths on College Campuses. In *Twelfth International AAAI Conference on Web and Social Media*.
- [48] Koustuv Saha, Asra Yousuf, Ryan L Boyd, James W Pennebaker, and Munmun De Choudhury. 2022. Social media discussions predict mental health consultations on college campuses. *Scientific reports* 12, 1 (2022), 123.
- [49] Steven Stack. 1987. Celebrities and suicide: A taxonomy and analysis, 1948-1983. *American sociological review* (1987), 401–412.
- [50] Shannon Wiltsey Stirman and James W Pennebaker. 2001. Word use in the poetry of suicidal and nonsuicidal poets. *Psychosomatic medicine* 63, 4 (2001), 517–522.
- [51] Elizabeth A Stuart. 2010. Matching methods for causal inference: A review and a look forward. *Statistical science: a review journal of the Institute of Mathematical Statistics* 25, 1 (2010), 1.
- [52] Benedikt Till, Florian Arendt, Sebastian Scherr, and Thomas Niederkrotenthaler. 2018. Effect of educative suicide prevention news articles featuring experts with vs without personal experience of suicidal ideation: a randomized controlled trial of the Papageno effect. *The Journal of clinical psychiatry* 80, 1 (2018), 13780.
- [53] Benedikt Till, Markus Strauss, Gernot Sonneck, and Thomas Niederkrotenthaler. 2015. Determining the effects of films with suicidal content: a laboratory experiment. *The British Journal of Psychiatry* 207, 1 (2015), 72–78.
- [54] Benedikt Till, Ulrich S Tran, Martin Voracek, and Thomas Niederkrotenthaler. 2017. Beneficial and harmful effects of educative suicide prevention websites: randomised controlled trial exploring Papageno v. Werther effects. *The British Journal of Psychiatry* 211, 2 (2017), 109–115.
- [55] Gary R VandenBos. 2007. *APA dictionary of psychology*. American Psychological Association.
- [56] Gaurav Verma, Ankur Bhardwaj, Talayah Aledavood, Munmun De Choudhury, and Srijan Kumar. 2022. Examining the impact of sharing COVID-19 misinformation online on mental health. *Scientific Reports* 12, 1 (2022), 1–9.
- [57] Qiaosi Wang, Koustuv Saha, Eric Gregori, David Joyner, and Ashok K Goel. 2021. Mutual Theory of Mind in Human-AI Interaction: How Language Reflects What Students Perceive About a Virtual Teaching Assistant. In *Proc. CHI*.
- [58] WHO. 2019. Suicide in the world: global health estimates.
- [59] Yunhao Yuan, Gaurav Verma, Barbara Keller, and Talayah Aledavood. 2022. The Impact of COVID-19 Pandemic on LGBTQ Online Communities. *arXiv preprint arXiv:2205.09511* (2022).