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Stories that Heal: Characterizing and Supporting Narrative for Suicide Bereavement

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Abstract

Clinical group bereavement therapy often promotes narrative sharing as a therapeutic intervention to facilitate grief processing. Increasingly, people turn to social media to express stories of loss and seek support surrounding bereavement experiences, specifically, the loss of loved ones from suicide. This paper reports the results of a computational linguistic analysis of narrative expression within an online suicide bereavement support community. We identify distinctive characteristics of narrative posts (compared to non-narrative posts) in linguistic style. We then develop and validate a machine-learning model for tagging narrative posts at scale and demonstrate the utility of applying this machine-learning model to a more general grief support community. Through comparison, we validate our model's narrative tagging accuracy and compare the proportion of narrative posts between the two communities we have analyzed. Narrative posts make up about half of all total posts in these two grief communities, demonstrating the importance of narrative posts to grief support online. Finally, we consider how the narrative tagging tool presented in this study can be applied to platform design to more effectively support people expressing the narrative sharing of grief in online grief support spaces.

Introduction

The loss of a loved one to suicide is one of the most challenging events a person can endure. It is a loss that is often unexpected, leading to feelings of hopelessness, powerlessness, guilt, and isolation (Cerel et al. 2014, 2019; Leaune et al. 2021; Mitchell et al. 2003; Neimeyer 2012; Neimeyer and Pfeiffer 1994; Shields, Kavanagh, and Russo 2017). The stigma of suicide is deeply internalized throughout social discourse (Hanschmidt et al. 2016; Pitman et al. 2017). Those undergoing bereavement after a loved one completes suicide (referred to as 'the bereaved') often grapple with an intense journey of grief and healing for the rest of their lives (Cerel et al. 2014; Mitchell et al. 2003; Shields, Kavanagh, and Russo 2017).

Although all grief is destabilizing, grief that occurs during the suicide bereavement process is especially devastating and isolating (Andriessen et al. 2019; Cerel et al. 2014, 2019). Due to the intensity of the loss, suicide bereavement is clinically understood as a type of grief that stretches beyond the typical healing processes (Krysinska and Andriessen 2013; Linde et al. 2017). The perceived loss of agency during the suicide bereavement process presents an additional obstacle to healing (Shields, Kavanagh, and Russo 2017; Mitchell et al. 2003; Neimeyer 2012; Pitman et al. 2017). Reclaiming one's agency is a fundamental focus and goal of clinical bereavement intervention.

In clinical settings, suicide bereavement support requires specialized therapeutic interventions. These interventions often take the form of group support, where people expressing similar traumatic responses can gather with one another and heal collectively. Group support is especially vital in reclaiming one's agency (Mitchell et al. 2003; Neimeyer 2012; Pitman et al. 2017). Research suggests that the most significant barriers to reclaiming the bereaved's agency are immense feelings of guilt and subsequent isolation felt from the bereaved's social support system (Leaune et al. 2021; Pitman et al. 2017). One important therapeutic intervention often utilized in clinical suicide bereavement groups to combat guilt and isolation and increase agency is narrative sharing (Neimeyer and Pfeiffer 1994).

The practice of narrative sharing has recently increased in prevalence outside of the clinical setting, informally, in social media grief support groups (Best, Manktelow, and Taylor 2014; Manikonda and De Choudhury 2017). *Narrative* is a mode of discourse that introduces events, states, and entities that are temporally related (Smith 2001). *Narrative* is the discourse that contains continuity in the form of a plot, where entities undergo state changes in the form of character development (Smith 2001).

Although clinical research has demonstrated that in-person narrative sharing facilitates positive bereavement outcomes (Mitchell et al. 2003; Neimeyer 2012; Sands, Jordan, and Neimeyer 2011), the degree to which this extends to online interactions is a developing area of study with critical ramifications for platform design. Research and design for grief support could benefit by more effectively understanding how patterns in the sharing of narrative in online suicide bereavement support spaces compare to the sharing of narrative in other grief support spaces. For instance, comparing the frequency of narrative sharing between suicide bereavement spaces and more general grief spaces could inform whether additional attention should be paid to tailoring platform design to support narrative sharing in suicide bereavement communities.

To provide initial insight into how patterns in the sharing of narrative in online suicide bereavement support spaces compare to the sharing of narrative in other grief support spaces, we study narrative-sharing practices on r/SuicideBereavement, a suicide bereavement community on the Reddit platform. We specifically ask:

1. What are the linguistic features of narrative posts within an online suicide bereavement community?
2. Do those linguistic features allow us to predict narrative posts in other grief support communities?
3. What do proportions of narrative posts within comparable grief communities tell us about the expression of narrative across different grief contexts?
4. What are the implications of those differences between different grief contexts to online platforms?

To address these questions, we first studied posts and their corresponding comments within the r/SuicideBereavement subreddit community. To begin, we surveyed and characterized the subreddit. We then developed a codebook for coding narrative posts and manually tagged a subset of 750 posts. We then conducted a computational analysis using multiple linguistic tools (VADER, Syuzhet, and LIWC). Within our subset of posts, we compared key linguistic features across narrative posts, non-narrative posts, and their respective comments.

Finding significant linguistic differences between narrative and non-narrative posts in our subset (for example, narrative posts contain significantly more values of social processes and past tense language than non-narrative posts according to LIWC measures), we then constructed a machine learning (ML) classification model to aid us in future narrative tagging at scale. We applied our model to our dataset of posts from r/SuicideBereavement and, after validating its accuracy again through manual coding, noted the proportion of narrative posts compared to non-narrative posts.

Seeking to compare the proportion of narrative posts between a suicide bereavement community and a more general grief support community, we then analyzed r/GriefSupport, a general grief support community on Reddit. First, we deployed our narrative tagging model on a randomized subset of posts from r/GriefSupport. Independently, we manually coded the same randomized subset of posts. We validated that the model accurately tags narrative in r/GriefSupport. We then determined the proportion of narrative posts compared to non-narrative posts in a substantial corpus of r/GriefSupport posts. We find that both r/SuicideBereavement and r/GriefSupport contain comparable proportions of narrative relative to their respective corpora.

By demonstrating that our model can accurately tag narrative posts and generate insights across multiple grief contexts (in this case, the proportion of narrative), we contribute a tool that can be used in future research to examine narrative across diverse communities. By finding that narrative posts make up a substantial proportion of the total number of posts in both communities, we empirically demonstrate the importance of studying narrative within future research on grief and loss.

Related Work

To inform our study design, we bring together (1) background on the suicide epidemic and social media, (2) clinical research on positive bereavement outcomes facilitated by bereavement support groups that utilize narrative therapy modalities, and (3) methodological background on natural language processing and narrative tagging.

The Suicide Epidemic and Social Media

In 2020, suicide was the 10th leading cause of death in the United States (American Foundation for Suicide Prevention 2022; Ramchand, Gordon, and Pearson 2021). On average, 132 people in the United States die by suicide daily (48,344 annually). In the United States, suicide is the 2nd leading cause of death for ages 10–34 and the 4th leading cause of death for ages 35–54. Suicide is not limited to the US or Western context, with suicide rates rising annually around the world (Yip, Zheng, and Wong 2022). A staggering number of people lose a loved one to suicide every year, with an estimated 54% of the US population bereaved by someone in their circle of friends or family completing suicide (American Foundation for Suicide Prevention 2022; Ramchand, Gordon, and Pearson 2021). Due to decreasing funding and clinician bandwidth, social support for suicide bereavement cannot keep up with the growing demand for support and resources. Recent research shows that social media platforms have begun to fill this gap (Krysinska and Andriessen 2013, 2017; Krysinska et al. 2019).

Social media has emerged as a critical space where grieving people can express their grief, share their mourning with others, and seek mental health support or resources within a community setting (De Choudhury et al. 2016; Doyle and Brubaker 2023; Luxton, June, and Fairall 2012). Across forums and virtual groups on platforms such as Reddit and Facebook, grieving users can find additional support beyond offline settings such as counseling or in-person support groups (Krysinska et al. 2019). In part, virtual community support supplements in-person support by providing the safety of anonymity, connection with other grievers from many different backgrounds and locations, and unique formats for storytelling such as video (Bailey, Bell, and Kennedy 2015). Beyond being a space where grieving users can access additional resources, the social community serves as a resource to support the bereaved on their journey.

Through exploring the relational dynamics of a community bound by a common traumatic experience, this paper expands on studies studying the communication practices of how suicide bereavement needs are expressed in online communities (Bailey, Bell, and Kennedy 2015; Bailey et al. 2017; Bell, Bailey, and Kennedy 2015; Krysinska and Andriessen 2017; Leaune et al. 2021; Perusse 2021).

Studying Narrative Communication Practices in Online Suicide Bereavement Support

Although some people bereaved by suicide choose to post on private blogs where there is no intended audience beyond themselves, many express themselves in public online support groups. Narrative sharing is a key communication practice in online support groups, such as the r/SuicideBereavement subreddit that this paper studies. By turning to the therapeutic affordances present in narrative sharing within offline bereavement support groups, we can begin to conceptualize possible therapeutic affordances of narrative sharing online.

In offline settings, clinical suicide bereavement support groups are a common and effective means of supporting loved ones (Mitchell et al. 2003; Neimeyer 2012; Sands, Jordan, and Neimeyer 2011). They take many forms, are of many sizes, and utilize diverse therapeutic modalities to achieve positive bereavement outcomes for participants (Neimeyer 2012). However, in recent years, using narrative sharing as an intervention—specifically, the practice of writing and sharing stories to assist participants in regaining agency—has emerged as "one of the central activities of survivors of suicide support groups" (Mitchell et al. 2003; Neimeyer and Pfeiffer 1994; Sands, Jordan, and Neimeyer 2011).

Growing out of a specific set of practices pioneered by Michael White and David Epston in the 1970s and 1980s, popularized as Narrative Therapy (White, Wijaya, and Epston 1990), recent interpretations by scholars such as Robert Neimeyer have taken these practices and tailored them to bereavement-specific contexts (Neimeyer 2012). In more recent research, narrative sharing has been proven to be a helpful way to achieve positive bereavement outcomes even when not paired with the specific Narrative Therapy interventions of White and Epston (Mitchell et al. 2003; Neimeyer 2012; Polkinghorne 1996).

In suicide bereavement groups, narrative sharing can lead to heightened well-being and a personal sense of community through sharing narratives of loss with others (Mitchell et al. 2003). Narrative sharing results in positive bereavement outcomes through the reclamation of *agentic narratives* created by the rewriting of a *dominant narrative* (Sands, Jordan, and Neimeyer 2011). Additionally, narrative sharing leads participants towards a decrease in *victimhood narratives* (Polkinghorne 1996). Polkinghorne and colleagues delineate *agentic narratives* as "depicting events in such a way as to suggest the narrator is in control, despite disruption by traumatic life events" and *victimhood narratives* as "depicting events affecting the narrator's life [as] controlled by outside forces" (Polkinghorne 1996).

Narrative sharing practices in this context consist of writing and sharing stories that allow participants to increase their capacity to express *agentic narratives* through externalizing the self to fit their story into a collective one, interfacing with deep emotion that might not be expressed outside of the story, and facilitating appropriate self-critique (Mitchell et al. 2003; Polkinghorne 1996; Sands, Jordan, and Neimeyer 2011).

Group support allows for greater visibility and a sense of community for the bereaved. Sharing one's narrative in a community setting allows one to re-author their story and drive new personal growth. Additionally, despite the nuances of different narrative-sharing practices, research by both Mitchell and Neimeyer asserts that, in suicide bereavement support groups, all narrative practices help move people towards positive bereavement outcomes (Mitchell et al. 2003; Neimeyer 2012).

Studying offline therapeutic communication practices as they occur in online spaces has been shown in prior research to provide insight on how platforms might be better adapted to serve those practices as they manifest online (Getty et al. 2011). Our research extends previous research studying online communication practices toward a goal of supporting future platform design that more effectively supports bereaved users.

Additional research has studied narrative sharing in online grief support settings (Andalibi 2020; Andalibi and Forte 2018; Antoniak, Mimno, and Levy 2019; Tangherlini and Roychowdhury 2020). For example, Andalibi and Forte (2018) studied narrative disclosure in online pregnancy loss support. However, social computing research to date has not studied narrative sharing in suicide bereavement groups. This study extends prior social computing research by adding suicide bereavement as a further area of study to understand how narrative grief support functions in online settings.

Lexicon Approaches and Bereavement Research

Previous research has utilized lexicon approaches to determine linguistic expression patterns in social media contexts. For example, Getty et al. (2011) used lexicon approaches to analyze the Facebook posts of bereaved individuals and found that mourners use memorialized profiles to continue their bonds with the deceased. Other research by De Choudhury et al. (2014) used lexicon approaches to build a tagging model for characterizing and predicting postpartum depression online. Additionally, Brubaker et al. (2012) used lexicon approaches to distinguish MySpace comments expressing emotional distress from comments not expressing emotional distress, noting that there are significant linguistic differences between the two. While previous research has used lexicon approaches to identify meaningful patterns in bereavement-related content, it has only focused on certain types of grief (*e.g.*, postpartum depression) or generalized expressions of grief (*e.g.*, emotional distress). This study expands previous research by applying lexicon approaches to a suicide bereavement context.

Lexicon Approaches and Narrative Tagging

Previous research has used computational natural language processing methods to construct tools that tag narrative. However, context and domain are important aspects of most of these projects. Put simply, what narrative looks like in other contexts, such as design storytelling (Salah, Chandrasegaran, and Lloyd 2022), is different than in grief contexts. We take inspiration from De Choudhury et al. (2014), who developed a post-tagging model for postpartum depression, in seeking to develop a novel classifier specifically for narrative tagging in the context of sharing grief narratives in online communities.

Ethics and Responsibility

We conducted this study in partnership with the moderator leadership of r/SuicideBereavement. While recognizing that this leadership group does not speak for the entire community, we obtained permission from the moderators to conduct this study and to name the specific subreddit in this article.

While the data in our analysis is public, the sensitive nature of our research area makes it important to note that any analysis of social media posts touches on personal lived experience. Users in this subreddit are often in active states of grief and bereavement, and, as such, we have taken the steps to anonymize all user information throughout the analysis process and have chosen not to include identifiable data in the report of our analysis.

We additionally acknowledge that the lead researcher has participated in this community for a number of years, both in an active posting capacity and in a passive observing capacity. As previous ethnographic research such as Feuston and Piper (2018) demonstrate, this pre-existing relationship helps to show investment in the community's well-being and helps to build trust with community leadership.

Lastly, we recognize that ethical decisions are implicit in the ways that we share the content of this study with our own research community. We note that to protect our readers from unnecessary harm, we have refrained from including specific language or scenarios that depict suicide.

Data

Our analysis of suicide bereavement narrative text is based on a corpus of 2,590 Reddit posts and their 16,502 comments from r/SuicideBereavement posted during 2021.

On Reddit, threads begin with a *post* from the original poster (OP), to which others (including the OP) can respond via *comments*. Posters are primarily identified through a chosen username, allowing them to control their level of anonymity. We selected Reddit due to the lead author's previous familiarity with the platform (including the subreddit) and prior research that shows Reddit to be a common social media platform where people often share mental health-related experiences and information while seeking and providing support (Tadesse et al. 2019; Xu et al. 2023).

We collected our dataset using the Pushshift.IO API and the PMAW Python module (Baumgartner et al. 2020). We filtered out any posts or comments that were removed, deleted, or blank, as well as threads without any comments. In addition to the text of the posts and comments themselves, our dataset included metadata such as the upvote ratio, post score, comment score, number of comments, and number of unique commentators.

Coding Narrative Posts

To perform a comparative narrative/non-narrative analysis of posts, we first needed to identify narrative posts.

There are diverse approaches to and definitions of narrative. For example, Tangherlini and Roychowdhury (2020) conceptualize narrative as a framework of actants, relationships, and sequence. Meanwhile, Antoniak, Mimno, and Levy (2019) note that a traditional definition of narrative is the oral histories one might tell to their community. For our current purposes, we turn to the work of Smith (2001) on narrative discourse, which defines narrative as having four characteristics: *temporality*, *advancement*, *tense interpretation*, and *entities introduced*. We use Smith's definition due to its explicit focus on temporality and tense, which are often referenced in offline narrative therapy settings as features that reveal ways that patients relate and integrate past traumatic events (Hall and Powell 2011).

Operationalizing Smith's characteristics, our codebook had four inclusion criteria: the presence of a plot, characters, the author as a character, and a clear beginning, middle, and end. Additionally, we included three exclusion criteria. Posts were marked as non-narrative that were: purely informational, entirely providing resources, or entirely composed of a question posed to the subreddit community.

To validate inter-rater reliability (IRR), 3 members of the team coded a random sample of 20 posts and achieved excellent agreement ($\kappa = 0.898$). After achieving a high IRR, two of the authors coded a total of 750 of the 2,590 posts. Of these posts, 276 (36.8%) were coded as narrative, while the remaining 474 (63.2%) were coded as non-narrative.

Calculating Linguistic Metrics for Narrative

Having established a reliable way of distinguishing narrative posts from non-narrative posts, our next objective was to determine whether computationally detectable linguistic patterns underlie these narratives. In this part of our study, we aimed to find and articulate the linguistic characteristics of narrative content.

We started by producing measures for all of our posts and comments using three different computational linguistic tools: VADER (Hutto and Gilbert 2014), Syuzhet (Jockers 2017), and LIWC (Tausczik and Pennebaker 2010). While sentiment analysis tools using deep learning and transformer architectures may offer higher performance on some sentiment analysis tasks than lexicon-based methods (Acheampong, Nunoo-Mensah, and Chen 2021; Do et al. 2019; Yue et al. 2019), we employ the latter because of their prevalence, parsimony, and interpretability. VADER is a dictionary-based tool for evaluating sentiment of language sampled from the internet. It has been used in a variety of academic natural language processing applications, including work in hate speech detection and the classification of offensive language (Davidson et al. 2017). Syuzhet, meanwhile, was used to determine the frequency of emotions—specifically anger, anticipation, disgust, fear, joy, sadness, surprise, and trust (Jockers 2017). Syuzhet has been employed for various contexts including analysis of TripAdvisor content, novels, and political language on Twitter (Naldi 2019). Finally, LIWC identifies the relative frequencies of linguistic markers such as personal pronouns, tense usage, affect, and other elements of linguistic style (Tausczik and Pennebaker 2010). LIWC is a common language analysis package that provides dictionaries for parts of speech and punctuation, as well as psychological, cognitive, and social processes (Pennebaker et al. 2015; Pennebaker, Francis, and Booth 2001; Tausczik and Pennebaker 2010). LIWC has previously been used for analyzing social media content (Brubaker et al. 2012; Getty et al. 2011). All three of these tools provide scores between 0 and 1 per each metric, specifying the proportion of words in the provided text that are part of the dictionary for a given measure.

Before starting our analysis on narrative posts within the subreddit, we followed the practice of similar scholarship (Jiang and Brubaker 2018) and confirmed that posts in this subreddit were distinct from Reddit-at-large. To create a corpus of "general" posts, we pulled 1,000 posts from across Reddit that were posted during the same period as the r/SuicideBereavement data and generated linguistic measures using our three tools. By not specifying a subreddit in the PMAW API we were able to get a quasi-random sample of posts from across Reddit.

We determined that there were significant differences between r/SuicideBereavement subreddit posts and general Reddit posts. Notably, subreddit posts contained substantially higher expressions of emotion and especially higher negative sentiment (VADER Negative: $U = 1620427, p < .0001$; LIWC sadness: $U = 1626949, p < .0001$). Additionally, subreddit posts contained higher expressions of past tense (LIWC past: $U = 1546602, p < .0001$), and pronoun use (LIWC pronoun: $U = 1614551, p < .0001$).

Linguistic Features of Interest

Throughout our analysis, we focused on the frequency of use of linguistic style features, sentiment and emotional expression, cognitive processes, and social processes.

Linguistic Style. The linguistic style features we examined included word count, pronouns, and tense use. Word count can act as a proxy for the amount of communication, where greater communication, unity, and positive feedback have been found to promote better health outcomes (Tausczik and Pennebaker 2010). Linguistic style, such as pronoun use and tense use, has been shown to reveal information about people's priorities, intentions, and thoughts (Tausczik and Pennebaker 2010). For example, patterns in pronoun use reveal who someone is attending to and information about the subject of attention.

For pronouns, we measured First Person Singular, First Person Plural, Second Person, Third Person Singular, Third Person Plural, and Indefinite pronouns. Heightened use of first person pronouns and decreased use of second and third person pronouns have previously been found to relate to depression (Pennebaker, Mehl, and Niederhoffer 2003). Additionally, previous research suggests that use of first person singular pronouns increases during moments of emotional upheaval (Pennebaker, Mehl, and Niederhoffer 2003). Tense use is an indicator of informality as well as need states (Pennebaker, Mehl, and Niederhoffer 2003). Linguistic style features are additionally linked to attentional differences such as who or what the author of a body of text is paying attention to (*e.g.*, a person using first-person singular pronouns may be demonstrating a self-focus in response to emotional pain (Wolf et al. 2007)).

Sentiment and Emotion. To assess expressions of sentiment and emotion, we examined sentiment features from VADER, emotion measures from Syuzhet, and LIWC's measures for affect.

LIWC's categories of emotion include the general amount of affect expressed in a body of text, along with categories for specific emotions such as anger, anxiety, and joy. Emotional expression measured by LIWC has been linked to how people react and cope with events. These categories have been used to measure to what degree the retelling of an event is negative or positive, according to its author (Kahn et al. 2007). The use of emotion words has also been used as a measure of the degree of psychological immersion the writer of a body of text may have relative to the experience they are describing.

In trauma contexts, greater use of emotion words has been shown to signal increased immersion in the traumatic event (Holmes, Arntz, and Smucker 2007). Emotion words have been positively correlated with other variables, such as pronoun use, auxiliary verb use, and negation use, demonstrating that the expression of emotion may be linked to additional insights around thinking styles and social awareness (Tausczik and Pennebaker 2010).

Cognitive Processes. We also examined measures of `cognitive processes` from LIWC. `cognitive processes` measures include words such as "cause", "ought", and other words linked to the active appraisal of insight. Originally used for analyzing political speeches, the `cognitive processes` metric can be thought of as measuring the extent to which someone differentiates among competing solutions (Tetlock 1981).

Higher values of `cognitive processes` have been shown to demonstrate a higher level of depth and complexity in reconstructing a past event (Tausczik and Pennebaker 2010). Causal words have been shown to create causal explanations to organize a person's thoughts when reevaluating a past event. Through the active processing that occurs in reconstrual, such as the sharing of narrative, studies on depression, such as that by Pennebaker, Mehl, and Niederhoffer (2003), have found that an elevated measure of causal and insight words can lead to greater health improvements.

Social Processes. Finally, we examined the social processes linguistically expressed in our corpus. The LIWC `social processes` category contains social verbs such as "talk" as well as references to social relationships such as "family" and "friend." The `social processes` category has been linked to insights around status, dominance, and social hierarchy (Kacewicz et al. 2009; Sexton and Helmreich 2000), along with social communication (Sexton and Helmreich 2000), group processes (Leshed et al. 2007), and honesty and deception (Pennebaker, Francis, and Booth 2001). `social processes` provides insight into how a person may be processing a traumatic scenario in a social context (Tausczik and Pennebaker 2010).

Post-Level Differences

We started by comparing narrative posts to non-narrative posts. The unit of analysis for these comparisons was a single post. We conducted a series of Mann-Whitney U tests to identify linguistic differences between post types, using the Holm-Bonferroni correction to account for repeated tests. Results are shown in Table 1.

Metric	Narrative	Non-Narrative	p	d	U
Word Count	341.322	148.156	***	0.901	105 889
Personal Pronouns	0.154	0.145	*	0.203	73 659
Third-Person Singular	0.046	0.026	***	0.675	92 402
First-Person Plural	0.009	0.006	***	0.262	84 118
Present tense	0.069	0.092	***	-0.601	43 794
Past Tense	0.067	0.048	***	0.643	90 206
VADER: Neutral	0.749	0.730	*	0.240	74 581
Affective Processes	0.059	0.070	**	-0.337	54 083
Inclusive	0.054	0.044	***	0.418	82 692
Social Processes	0.126	0.106	***	0.388	80 768
Family	0.014	0.010	***	0.251	83 695

Table 1: Mann-Whitney U-test results and descriptive statistics of narrative and non-narrative posts. All reported results are metrics generated by LIWC unless otherwise noted. Only results with a small or larger effect size ($|d| > 0.2$) are reported. *$p < 0.001$, **$p < 0.0001$, ***$p < 0.00001$

Our results indicate that linguistic style (`word count`, `pronouns`, and `verb tense`) and social processes (`social processes` and `family`) are strong markers for narrative posts, as are `inclusive`, and emotion (`affective processes`) to a lesser extent.

Linguistic Style. Narrative posts are significantly longer in length than non-narrative posts ($U = 105889.5; p < 0.00001$), with an average length of 341.32 words compared with 148.16 words for non-narrative posts.

Each of the three pronoun metrics was significantly higher in narrative posts. For pronouns, we found significant differences for personal pronouns (*e.g.*, I, them, her, etc.; $U = 73659; p < 0.001$), first-person plural pronouns (*e.g.*, we, our, etc.; $U = 84118.5; p < 0.00001$), and third-person singular pronouns (*e.g.*, he, she; $U = 92402; p < 0.00001$).

We also examined use of past, present, and future tense. Significant differences existed for present tense ($U = 43794; p < 0.00001$) and past tense ($U = 90206; p < 0.00001$), but not future tense ($U = 65898; p = 0.862$). Present tense was less common in narrative posts, while past tense was more common.

Sentiment and Emotion. We found no significant differences in sentiment (VADER's `positive` and `negative` measures), save `neutral` ($U = 74581; p < 0.001$), which was more common in narrative content. While initially surprising, the higher `neutral` scores are likely due to the amount of neutral language included while sharing narrative details.

None of the comparisons of Syuzhet's measures (`anger`, `anticipation`, `disgust`, `fear`, `joy`, `sadness`, `surprise`, `trust`) were significantly significant.

Likewise, comparisons using LIWC measures were largely not significant, including `positive emotion`, `negative emotion`, `anger`, `anxiety`, and `sadness`. However, one LIWC measure was: `affective processes`, a broad measure that captures emotionality. We found that narrative posts contain less `affective processes` than non-narrative posts ($U = 54083.5; p < 0.0001$).

The general lack of findings for sentiment and emotion was surprising, considering that previous studies have shown an increase in emotion while recounting traumatic events (Tausczik and Pennebaker 2010). There may be two possible explanations grounded in the observation that in comparison to non-narrative posts, the narrative posts in our corpus are significantly longer. First, because our tools measure the proportion of words present in the text, an otherwise high number of emotional words may be diluted in longer narrative posts. Second, it may be that narrative is a vehicle of exposition that uses a story to 'show' and not 'tell' emotion—a contrast to shorter posts, which may be more directly telling or may express their emotions using more direct language.

Cognitive Processes. We tested for all LIWC measures related to cognitive processes, including: `cognitive mechanics`, `insight`, `causation`, `discrepancy`, `tentative`, `certainty`, `inhibition`, `inclusive`, and `exclusive`. Of these nine measures, we found that `inclusive` language was significantly higher in narrative posts ($U = 82692.5; p < 0.00001$). `inclusive` is measured by words such as "and", "with", and "include." Previous studies such as Creswell et al. (2007) show that greater values of the `inclusive` variable are linked to positive self-affirmation, positive group affirmation, cognitive insight, the discovery of meaning, and collaboration with groups.

Social Processes. We compared all LIWC measures for social processes and found significantly greater usage of `social processes` ($U = 80768; p < 0.00001$) and `family` ($U = 83695.5; p < 0.00001$) language in narrative posts.

`social processes` includes words such as "mate", "talk", "they", and "child." It has been shown to measure: who has more status, whether a group is working well together, if someone is being deceptive, and the quality of a close relationship (Tausczik and Pennebaker 2010). Higher levels of the `social processes` category have been shown to be correlated to positive group collaboration (Pennebaker, Francis, and Booth 2001). Seeing higher expressions of `social processes` in narrative posts may suggest that narrative posts direct attention to social dynamics within their narrative, a metric linked to positive health outcomes (Pennebaker et al. 2015).

Increased use of `family` (*e.g.*, "daughter", "husband") has been shown to signify more communication, more unity, and positive feedback (Tausczik and Pennebaker 2010), which in turn have been tied to better group performance and group health outcomes (Creswell et al. 2007; Kahn et al. 2007; Pennebaker et al. 2015).

Comment-Level Differences

Following our analysis of posts, we compared comments on narrative posts to comments on non-narrative posts. Our objective here was not to describe narrative in commments, but rather to describe what linguistic practices look like in response to narrative vs. non-narrative posts.

Our unit of analysis for this phase was the set of comments responding to a single post. We generated metrics for each of the individual comments, and then averaged these scores to create post-level comment metrics. Identical to our analysis of posts, we conducted a series of Mann-Whitney U tests to identify linguistic differences between comment types, again utilizing the Bonferroni correction. Significant results are summarized in Table 2.

The results from our U-tests indicate that linguistic style (word count and third-person singular pronoun use) and social processes (`social processes`) are strong markers for narrative comments.

Linguistic Style. While examining linguistic style in narrative comments, we once again focused on word count, tense, and pronoun usage. We also examined the number of comments and unique authors each post received.

We found that comments on narrative posts have a higher average word count than comments on non-narrative posts ($U = 81601; p < 0.00001$). The average word count for narrative comments is 89 (vs. 70 for non-narrative).

We found no significant results when considering the number of unique comments ($U = 69256; p = 0.177$) or unique authors ($U = 68865.5; p = 0.224$). Likewise, we found no significant differences in tense usage.

When examining pronouns, we found a difference in the usage of third-person singular pronouns (*e.g.*, he, she, etc.; $U = 78994; p < 0.00001$), with greater expression of third-person singular pronouns in comments responding to narrative posts. No other differences in pronoun measures were statistically significant.

Sentiment and Emotion. We found no significant differences.

Cognitive Processes. We found no significant differences.

Social Processes. We tested for all LIWC measures for social processes and found significant differences for one metric: `social processes` ($U = 78667; p < 0.001$). While the difference is small, the elevated level of social processes language may suggest that comments on narrative posts demonstrate more positive feedback than comments on non-narrative posts.

Interpreting Linguistic Differences in Narrative Content

The results of language use analysis suggest that narrative posts differ significantly from non-narrative posts in linguistic style and social processes. Our findings show that key linguistic features of narrative posts include: (1) additional attention to collective/social language, and (2) additional attention to the past.

To better understand and contextualize the social implications of these distinctions, and especially how narrative may be facilitating positive bereavement outcomes in r/SuicideBereavement, we link these insights to narrative therapy outcomes. Additionally, by examining the social implications of linguistic patterns in narrative posts, we foreground the features that will be used as the foundation for the ML narrative classifier we present in the next section.

Collective Language: Additional Attention on Social Relationships. Narrative posts yield significantly higher values of `social processes`, `family`, and `inclusive` metrics than their non-narrative counterparts. Narrative posts also yield significantly higher values of first-person plural pronouns ('we'). These higher values may signify that narrative posts are distinct in their use of collective social language. Supporting the social focus of narrative posts, narrative comments similarly express higher values of `social processes`. These higher values may additionally mean that comments on narrative posts, similar to narrative posts themselves, promote group collaboration.

The `social processes` metric can serve as an indicator of the quality and characterization of a person's relationship with a community (or other social units) (Mitchell et al. 2003). Previous research by Sexton and Helmreich (2000) in non-health settings has demonstrated that greater degrees of `social processes` expressed in bodies of text may promote better group cohesion and open engagement within a group sharing setting. This is perhaps the case in bereavement settings as well. The language captured by `social processes` and `family` metrics has additionally been shown in previous research to foster collaboration with family, friends, and outside community (Linde et al. 2017; Shields, Kavanagh, and Russo 2017; Tausczik and Pennebaker 2010). That both narrative posts and their comments have a higher level of `social processes` may additionally mean that posting a narrative might inspire comments that reinforce positive social dynamics in the group or subreddit.

The `inclusive` metric can indicate how an author of a text is cognitively reflecting on social processes. Higher levels of the `inclusive` metric have been linked to openness or seeking support in times of crisis or depression (Pennebaker, Mehl, and Niederhoffer 2003). Higher `inclusive` measures, previously correlated with positive group affirmation and collaboration with groups (Creswell et al. 2007), may also demonstrate that narrative posts pro-

Metric	Narrative	Non-Narrative	p	d	U
Word Count	89.56	69.61	***	0.330	81 601
Third-Person Singular	0.018	0.013	***	0.280	78 994
Social Processes	0.136	0.124	*	0.211	78 667

Table 2: Mann-Whitney U-tests results and descriptive statistics of narrative and non-narrative comments. All reported results are metrics generated by LIWC. Only results with a small or larger effect size ($|d| > 0.2$) are reported. *$p < 0.001$, **$p < 0.0001$, ***$p < 0.00001$

mote positivity in the subreddit community and help maintain spaces that engender positive affirmation.

The higher frequency of first-person plural and third-person singular pronoun metrics may indicate that the authors of narrative posts are situating themselves within a particular social context. Their use of third-person singular pronouns may indicate that they are talking about the deceased and/or other actors pertinent to the story. Their use of first-person plural pronouns suggests that authors are referring to others who were involved in the scenario and with whom they are connected (Neimeyer 2012; Neimeyer and Pfeiffer 1994).

The focus on ‘we’ in bodies of text has been linked to individuals taking into account a wider support system (Neimeyer 2012). The focus on ‘we’ in addition to ‘I’ may mean that the authors of narrative posts are similarly incorporating others into their own story of loss, an intervention often employed in bereavement groups.

In bereavement narrative therapy support groups, a key benefit of storytelling comes from the opportunity for the author of a story to integrate the deceased into the bereaved’s own narrative of loss (Mitchell et al. 2003). This integration is often invited through either expressing empathy for what the deceased may have experienced (*e.g.*, ‘I think this is why they did this and what they may have been struggling with at the time’), or writing themselves into the overall story of loss (*e.g.*, ‘we used to count on each other’, ‘we were best friends’). By integrating the deceased into the bereaved’s own narrative of loss, the bereaved person is better able to see the deceased as a continued part of their world after suicide. Narrative sharing in this subreddit may be facilitating an opportunity to positively process the traumatic experience of loss by integrating the bereaved.

Attention on the Past. Narrative posts use higher levels of past tense and lower levels of present tense language. While these patterns make sense considering our manual coding parameters (*i.e.*, narrative requires discussion of the past), it is notable that this usage is computationally detectable.

Other studies have demonstrated that patterns in verb tense expression can reveal the temporal focus of attention. Pennebaker, Mehl, and Niederhoffer (2003) explain that attention to the past has been linked to expressions of coping during intense episodes of grief. Moreover, previous research focused on traumatic experiences has found that a focus on the past was a key marker when they observed the reauthoring of stories (Mitchell et al. 2003). In clinical practices surrounding narrative sharing, looking back and reflecting on the past has been specifically linked to supporting the bereaved (Mitchell et al. 2003; Neimeyer and Pfeiffer 1994).

In instances of suicide bereavement, a situation of trauma in which it is difficult for a person to remove themselves from intense bouts of grief in the present, the ability to reinterpret the past allows the bereaved to regain agency of their own narratives (Neimeyer 2012). In narrative posts, attention to the past, through use of the past tense, creates a separation between the emotional pain of past traumatic moments and the present (Hanschmidt et al. 2016; Mitchell et al. 2003).

Developing a Classifier for Narrative Posts

Having identified linguistic differences between narrative and non-narrative posts, we developed a classifier to identify narrative posts.

Model	Accuracy	F1	Precision	Recall
XGB	0.74	0.70	0.81	0.61
LogReg	0.76	0.70	0.90	0.57
k-NN	0.63	0.57	0.66	0.51
GaussianNB	0.68	0.73	0.62	0.88
BernoulliNB	0.75	0.77	0.71	0.84
Ensemble	0.80	0.78	0.84	0.73

Table 3: Classification metrics of post-level classifiers in r/SuicideBereavement

We started by creating a series of base models (XGBoost, Logistic Regression, k-Nearest Neighbors, Gaussian Naive Bayes, and Bernoulli Naive Bayes) to evaluate which algorithms would perform best with our dataset. The features that went into these models included the VADER, Syuzhet, and LIWC metrics on the post level. We used the 750 previously tagged posts for training our models and manually coded an additional 100 posts, which we used to test the accuracy of our classifiers. Finally, we created an ensemble model and reached an overall accuracy level of 0.80. Performance metrics for each model can be seen in Table 3.

After obtaining adequate accuracy for our model, we applied the model to the entire r/SuicideBereavement corpus of posts to determine the proportion of posts that were narrative. We found that of the total posts ($n = 2,590$), 48.5% ($n = 1,256$) were classified as narrative. This percentage was higher than what we observed during manual coding,

Metric	Narrative	Non-Narrative	p	d	U
Word Count	339.46	99.42	***	1.347	2270
Third-Person Singular	0.044	0.020	***	1.347	1888
Present tense	0.071	0.112	***	−0.772	601
Home	0.007	0.0014	***	1.043	2020

Table 4: Mann-Whitney U-test results and descriptive statistics of narrative and non-narrative posts in 100 posts sampled from r/GriefSupport. All reported results are metrics generated by LIWC unless otherwise noted. Only results with a small or larger effect size ($|d| > 0.2$) are reported. *$p < 0.001$, **$p < 0.0001$, ***$p < 0.00001$

but also confirms our earlier finding about the prevalence of narrative in this context.

Classification in Other Grief Contexts

After determining the accuracy of our model in r/SuicideBereavement, we took the final step of determining how specific our model was to suicide by testing our model in another online grief context: the r/GriefSupport subreddit.

We collected a year's worth of posts from r/GriefSupport from the same period of time as our previous dataset (2021–2022; $n = 12,805$).

We then randomly sampled 100 posts, manually coded them as narrative vs. non-narrative, and generated lexical metrics. To describe this dataset, we enumerate significant differences in Table 4.

Comparing the manual coding and machine classification resulted in an 84% agreement, suggesting that our ensemble classifier performs well within online grief support contexts and is not specific to suicide bereavement ($Accuracy = 0.84$, $F1 = 0.78$, $Precision = 0.83$, $Recall = 0.89$).

As a last step, we ran our classifier on the entire r/GriefSupport dataset and found that 49.7% ($n = 6,363$) of the posts contained narrative—a similar level to r/SuicideBereavement at roughly half of the total posts.

The prevalence of narrative in both contexts suggests that narrative is an important element of communication in online grief support communities. However, it is unclear how these communities support narratives, either socially or technologically. The presence of narrative—and a way to reliably detect it—suggest important paths forward, which we detail in the rest of this paper.

Promoting Content to Support Narrative Engagement

To more effectively facilitate online support of the expression of grief narratives, it is vital to understand when, where, and in what form narratives occur, and to design platforms that support appropriate engagement around these narratives. Narrative therapy interventions in clinical settings often require specialized spaces to support the narrative sharing of grief, narrative sharing spaces that are specifically designed to generate positive bereavement outcomes. We have demonstrated that narrative is prevalent in online grief support communities. However, narrative is being shared amongst other expressions that are non-narrative. Grief narrative shared online, outside of the structure provided by a clinical setting, might benefit from specialized spaces. One can imagine that specialized narrative-sharing spaces, modeled on highly facilitated in-person spaces, could be constructed in online contexts to facilitate these outcomes more effectively.

By designating specific spaces to share and respond to narrative posts, people sharing their stories can attain a sense of community through shared connection around and engagement with their stories. People responding to stories in this kind of narrative-focused space might be more likely to respond in constructive ways (*e.g.*, supportive comments) and/or be provided with guidance about appropriate responses informed by successful clinical interventions. For example, one can imagine a subreddit specifically dedicated to sharing suicide bereavement narratives that displays a list of types of responses that have been clinically demonstrated as most helpful on its sidebar. In such a community, moderation can be conducted on a more granular level, giving clear instructions to moderators to remove types of comments that have been clinically determined to be harmful.

Qualitative research on narrative grief disclosure has previously suggested that specialized spaces can be important for effective community support of loss (Andalibi 2020; Andalibi and Forte 2018). Our model presents a tool that could enable designers to support such spaces by classifying posts to ensure they are shared in appropriate specialized communities. That said, we acknowledge that designing automated tools to determine the appropriateness of a post could potentially cause unintended harm, necessitating further research on the design applications of automated narrative tagging in online communities.

Another benefit of classifying grief narratives is the possibility of protecting those who would be harmed by exposure to graphic or re-traumatizing stories. Many suicide bereavement narratives contain graphic details of a death or loss—or stories of how the traumatic loss of a loved one has triggered suicidal thoughts in the person posting. To the extent that these stories can harm people in the community seeking other forms of content, we can imagine ways that narrative classifiers in this context could be used to avoid potentially retraumatizing these people.

Specifying certain spaces as narrative-sharing spaces can allow users to consent to the type of content they will be exposed to, giving community members greater agency in choosing how and where they participate in providing support. Specifying certain spaces as narrative-sharing spaces can allow authors of narrative posts to more intentionally consent to post their sensitive stories with others specifically looking to support them.

It is possible that using our model to inform the creation of specialized spaces may have utility outside of social media spaces. For example, a suicide bereavement hotline may be able to use automated tagging to match proper support to users depending on how they are linguistically expressing their grief.

Of course, creating entirely new spaces for narrative sharing may only sometimes be prudent. For example, r/SuicideBereavement already has a critical mass of dedicated community members, and starting a new community may split the community as it currently stands. In these cases, the linguistic features we identified and the classifier we developed may prove useful if used to enable existing communities to identify narrative posts more easily. For example, filtering the display of narrative posts may allow some members of the community to identify and provide important support while others can avoid exposure to graphic or retraumatizing content.

Additional benefits to post classification and filtering features driven by community-level values are numerous. For example, one can imagine how the implementation of these methods can improve the ability of a platform to identify, extract, and promote a dynamic subset of "exemplar" posts offered to newcomers to more quickly orient themselves to the norms and practices of the community. This approach stands in contrast to existing implementations, which simply present a feed populated with whatever content happens to be "trending" or "popular" at a particular moment in time.

Limitations

Our study has several notable limitations. First, using computational linguistic approaches brings a set of limitations. Specifically, the tools we used rely on manipulating and weighting language variables that are not consistent across social and cultural contexts. LIWC for example, while frequently used in research contexts, is a dictionary-based tool that fails to capture contextual differences and certain subtleties of language, such as sarcasm. Additionally, all three of the tools we used are English-specific and do not capture linguistic features of languages beyond English. While the content we analyzed was all in English, our insights should not be generalized to other languages.

A further limitation in this study's generalizability is that the data used in this study were collected from a single subreddit, with our model tested on a single additional subreddit. Although our model had high accuracy when we validated it on r/GriefSupport, we did not validate our model on additional communities. Future work could build on this research by comparing the linguistic features of narratives across additional subreddits and platforms where grief is expressed.

This study focuses on linguistic features (such as pronoun use and tense) as predictors of narrative content. While linguistic features are effective in determining factors such as tense and affect quite well, they are not able to take into account certain other nuanced factors such as context and authorship. Future work should apply additional methods to provide insight into factors such as context and authorship, such as a systematic qualitative content analysis of narrative posts tagged by the linguistic model.

Conclusion

Expressing grief narratives is an important clinical intervention for people who have lost a loved one to suicide. Narrative sharing is one way that people use storytelling in offline clinical support groups to regain agency and heal in the wake of losing a loved one to suicide. Online grief support communities on social media platforms are emerging spaces in which grief narratives are shared and responded to by community members. Because of the potential for online platforms to be spaces of support for people seeking healing through the sharing of their grief narratives online, platforms can enhance the effectiveness of these uses through intentional design. To begin to determine what effective support may look like, we conducted a computational linguistic analysis of a suicide bereavement community. This analysis resulted in the identification of a linguistic signature for narrative posts. We found that narrative posts are distinctly characterized by (1) additional attention to collective/social language and (2) additional attention to the past.

Operationalizing the linguistic signature, we created a machine-learning model to identify narrative posts at scale. We applied this model to a second grief support community, validating its accuracy and determining that narrative posts make up almost half of the content posted to both of these similar-but-distinct grief support communities. In our discussion, we examined ways that platforms may more effectively support narrative sharing online, namely through establishing specialized narrative support spaces.

This study contributes a computational tool for more effectively identifying narrative expression in grief support based on the linguistic signature of these posts. Additionally, this study contributes initial reflections on pathways for platforms to more effectively support narrative sharing in grief support spaces, specifically the implementation of specialized spaces that intentionally attend to the needs of narrative expression.

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Paper Checklist

1. Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? Yes
2. Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? Yes
3. Do you clarify how the proposed methodological approach is appropriate for the claims made? Yes
4. Do you clarify what are possible artifacts in the data used, given population-specific distributions? Yes
5. Did you describe the limitations of your work? Yes, see Limitations section
6. Did you discuss any potential negative societal impacts of your work? Yes, we discuss the ethical challenges of utilizing natural language processing for conducting research on and with communities for grief support. We additionally discuss our methods for addressing those challenges.
7. Did you discuss any potential misuse of your work? Yes, see Ethics and Responsibility section
8. Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? Yes, see Ethics and Responsibility section
9. Have you read the ethics review guidelines and ensured that your paper conforms to them? Yes