How Do You Thrive: Exploring Expressions of Positive Psychological Concepts and Post-Traumatic Growth on Reddit via Text Mining

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Abstract

Objective: Psychological trauma can lead to debilitating health outcomes but can also facilitate personal growth. Researchers usually study post-traumatic growth (PTG) with small samples in real-life settings, showing consistent correlations with positive psychological concepts (PPCs). Despite the widespread use of social media for social support, there is a lack of research on textual markers connecting PPCs and PTG in online forums, calling for a closer investigation.

Methods: A total of 1,000 threads and 4,519 comments were scraped from a popular trauma-related subreddit posted over a one-year period. Linguistic Inquiry and Word Count (LIWC) and text mining procedures were used to determine the frequency of preselected PPCs and emerging related terms. Sentiment and emotional tone were estimated via lexicon-based sentiment analyses and LIWC, adjacent to cognition, affect, sociality and health categories. Differences between posts with PPCs and posts without were tested using chi-square and *t*-tests.

Results: The study identified 194 terms related to the 57 preselected PPCs in nearly 60% of all investigated posts. From all PPCs, the tokens *thank*, *love*, and *friends* were most frequently observed. Overall, social PPCs like *positive relationships* were represented the most. Chi-square and *t*-tests showed that posts with PPC expressions conveyed more positive sentiment and tone than those without. Both groups tended towards using more negative than positive emotion words. LIWC revealed that posts with PPCs used on average more social and affect words than posts without. Conversely, cognitive terms were more prevalent in posts without PPCs.

Conclusion: This study is one of the first to research natural PPC expressions and their textual relation to PTG in trauma-related online forums. Key findings highlight the relevance of social dimensions in online forums and expressions of gratitude, love, and hope which might contribute to fostering PTG in trauma-related online communities.

How Do You Thrive: Exploring Expressions of Positive Psychological Concepts and Post-Traumatic Growth on Reddit via Text Mining

We may not be responsible for the world that created our minds, but we can take responsibility for the mind with which we create our world – Maté (2018, p. 396)

Psychological trauma (hereafter called *trauma*) is a major source of human suffering. Stemming from old Greek meaning wound, trauma can be defined as "any disturbing experience that results in significant fear, helplessness, dissociation, confusion, or other disruptive feelings intense enough to have a long-lasting negative effect on a person's attitudes, behavior, and other aspects of functioning" (American Psychological Association, 2018, first paragraph). As a consequence, trauma can drastically inhibit an individual's quality of life, often associated with post-traumatic stress (PTS). PTS is commonly accompanied by intrusions, avoidance behaviour, distressing thoughts, rapid mood changes, and increased irritability (Bohlmeijer & Hulsbergen, 2018). In severe cases, PTS is eventually diagnosed as post-traumatic stress disorder (PTSD), which can comprise vivid intrusions of traumatic memories such as nightmares and flashbacks accompanied by overwhelming emotional and physical sensations (World Health Organisation (WHO), 2023).

Post-Traumatic Growth

Yet, trauma can also be a vehicle for personal growth. Post-traumatic growth (PTG) refers to psychological benefits gained after and because of a traumatic event (Calhoun et al., 2022; Clay et al., 2009). Despite frequently being confused with resiliency, which describes bouncing back to one's usual baseline well-being after having faced adverse events (Clay et al., 2009), PTG goes beyond previous levels of well-being. Specifically, PTG denotes an effective and productive adaptation to past adverse life circumstances, leaving the affected individual with advantageous long-term functional behaviour and improved psychological states compared to before experiencing the adversity (*growth*; Bohlmeijer & Hulsbergen, 2018; Clay et al., 2009). Growth can express its positive characteristics in various life-domains such as in finding meaning and purpose in life, losing the fear of death, or feeling a deeper sense of connection with the self, others and nature (Bohlmeijer & Hulsbergen, 2018). Those beneficial effects have been empirically observed following a range of traumatic events from sexual assault, car crashes to bone marrow transplantations (Tedeschi & Calhoun, 2004).

The PTG phenomenon has been extensively studied since the mid-1990s, most prominently by Tedeschi and Calhoun (Tedeschi & Calhoun, 1995; Tedeschi & Calhoun, 1996; Tedeschi & Calhoun, 2004) who later developed the PTG-Inventory (PTGI; Tedeschi & Calhoun, 1996). The PTGI is a 21-item scale assessing PTG across the five dimensions of *new possibilities, relating to others, personal strength, spiritual change,* and *appreciation of life* (Tedeschi & Calhoun, 1996) and is frequently applied in clinical and academic contexts (Calhoun & Tedeschi, 2012).

Positive Psychological Perspectives on PTG

Due to PTG's close relationship with positive changes in life and its focus on flourishing, rather than pathological dysfunction, it can be considered a positive psychological concept (PPC; Bohlmeijer & Hulsbergen, 2018). Positive psychology is a broad psychological discipline investigating a variety of PPCs which contribute to optimal psychological functioning, such as hope (e.g., Rand & Cheavens, 2012), gratitude (e.g., Kerry et al., 2023) or the identification and use of one's character strengths to improve overall well-being (e.g., Linley et al., 2010; Peterson & Seligman, 2004). Positive psychology's investigation of human well-being has coined a variety of new mental health and research fields (van Zyl & Rothmann, 2022), including interventions specifically promoting PTG in trauma treatments (Calhoun & Tedeschi, 2012; Bohlmeijer & Hulsbergen, 2018).

Academic literature consistently demonstrates correlations between PTG and various PPCs. For example, gratitude and hope have been found to correlate with PTG, likely because they contribute to promoting beneficial health outcomes (Confino et al., 2023), whereas high resiliency was identified as a potential preventive factor of PTS, buffering against adverse trauma-related outcomes (Vieselmeyer et al., 2017). Additionally, self-forgiveness was found to promote PTG among individuals bereaved by suicide-losses via cognitive and interpersonal mechanisms (Gilo et al., 2020). Furthermore, the social component is essential in several positive psychological theories. For instance, Seligman (2011) developed the PERMA model, which emphasises the importance of supportive *relationships* in achieving happiness, and Deci and Ryan (2008) identified *relatedness* as a core human need in the self-determination theory. In line with these theories, social support is recognised to be vital in mitigating PTSD risk (Brewin et al., 2000), suggesting an association between multiple socially rooted PPCs and inhibition of

PTSD development, and eventually, PTG. To receive this social support, many individuals nowadays turn to social media (Hanley et al., 2019).

The Role of Social Media in Fostering PTG

People who feel affected by trauma themselves, directly or indirectly, often engage on social media platforms to educate, discuss, and connect with fellow sufferers. Online mental health forums are increasingly used as support networks by younger generations worldwide and serve as the first source of mental health information for many (Hanley et al., 2019). Despite the rising shift to social media for social support and its acknowledged link in preventing PTSD development (Brewin et al., 2000), only a few studies have yet investigated PTG and its relation to expressions of PPCs in social media posts. For instance, the connection with fellow sufferers and stimulation of hope and meaning were identified in the qualitative phenomenological study by Liao Siling et al. (2021) as curing factors expressed by users in trauma-related online forums. Their results affirm that PPCs, such as feeling a connection (as in relatedness), hope, and meaning, were partially responsible for their improved well-being. Hence, text-based communication in online forums appears to stimulate certain PPCs, potentially fostering PTG.

Investigating PTG linguistically might offer new possibilities to understand and foster PTG in digital contexts, and especially online forums seem promising for that purpose. Some platforms are frequently studied and even recommended for textual mental health research (Cichosz, 2018), such as Reddit (Grant et al., 2017). Online forums like Reddit incorporate vast amounts of natural textual data in the form of threads and comments. Those posts offer a unique possibility to explore narratives without common methodological limitations imposed by researchers and the nature of questioning (i.e., recall bias; observer bias; interviewer bias) in traditional research designs. Specifically in trauma research, where trauma-affected respondents are regularly burdened by surveys (van der Velden et al., 2013), social media research in forums can have improved ethical feasibility because of its unobtrusiveness.

Researching Social Media

Researchers have traditionally used qualitative methods to study social media posts. Conventional qualitative research, however, shows major limitations when investigating large textual corpora such as those produced by online forums. Manual coding for instance requires much effort and time (Holtz et al., 2012), and often lacks reproducibility (Humphreys & Wang, 2017). With recent developments in natural language processing (NLP), latent information can be effectively extracted from unstructured textual data using NLP algorithms and automated machine learning computations with *text mining* (e.g., Grant et al., 2017; Humphreys & Wang, 2017; Sik et al., 2021; Yu et al., 2014; Zhang et al., 2015). Text mining is especially valuable for analysing online textual data, like forum posts (Sik et al., 2021), due to its ability to effectively handle big data corpora of natural language (Grant et al., 2017; Zhang et al., 2015). Text mining operations could generate insights into how prominent specific words or PPCs are represented in forums and which sentiments are associated with posts using these words. Furthermore, psycholinguistic dictionaries as used in text analysis software like Linguistic Inquiry and Word Count (LIWC; Francis & Pennebaker, 1992) can explore more complex constructs and emotions conveyed in text.

LIWC and Textual Markers of PTG

LIWC can indicate the degree to which text expresses psychological concepts such as the degree of cognition, affect, or tone conveyed in text. Researchers regularly apply the text analysis tool in sentiment and emotion word analyses of natural language in social media (Beasley & Mason, 2015; Sametoğlu et al., 2023). Increasingly, however, LIWC is also used to assess psycholinguistic constructs from text which may represent narratives of PTG (Mathews, 2019, Zheng et al., 2019). For instance, Scrignaro et al. (2017) utilised the text analysis program to analyse the use of positive and negative emotion words in cancer patient narratives, and Norman et al. (2020) used it in online PTG interventions for veterans to analyse writings for tone, authenticity, confidence, and analytical thinking. Despite LIWC's prominent and popular use in linguistic and textual research (Czarnek & Stillwell, 2022; Hartmann et al., 2019; Hickman et al., 2020; Pennebaker et al., 2022), only a few studies investigated the PTG phenomenon with tools like LIWC on texts posted on social media.

Most of the present textual studies were done with expressive writings from students or severely traumatised populations. These studies found that the use of words from LIWC's cognition category (like *reflecting*) correlates with PTG, due to representing meaning-making and therewith integration of the traumatising event (Mathews, 2019; Park, 2010; Zheng et al., 2019). For instance, one study using LIWC 2007 by Zheng et al. (2019) found that the frequent use of *causal* and *insight* words (such as *because* or *reason*) from the cognitive category of LIWC dictionaries significantly correlates with meaning-making. In turn, meaning-making predicted higher scores on the PTGI scale in traumatised students. These studies are some of the very few which provide the first indicators of textual markers of PTG, mirroring the scarce knowledge about this promising topic and simultaneously demonstrating the exceptional value of using text mining methods and LIWC analyses to investigate it linguistically.

Text Mining Reddit to Explore Expressions of PPCs and PTG

The high adoption of online mental health forums for social support in trauma recovery calls for more attention to exploring PTG through a linguistic lens. However, research still predominantly investigates PTG through methods such as interviews, scales like the PTGI, or systematic reviews of correlational studies (Henson et al., 2021). There is yet a lack of research on the natural expressions of PPCs and PTG in online narratives from trauma-related forums.

This study was conducted to explore textual expressions of PTG and PPCs in a trauma-related subreddit. The study's main objective was to investigate how online forum members use specific concepts commonly studied by positive psychology in their natural textual communication with other members via posts. It first examined the frequency of subreddit members' linguistic expressions of a selection of core PPCs and in which affective context they occur. Since this study is one of the first to investigate a broad selection of PPCs in a trauma-related forum, a measure of subjectivity like sentiments and emotional tone can give insights into the affective context in which PPCs are embedded. Secondly, psycholinguistic markers of PTG such as cognitive words (e.g., Zheng et al., 2019) were investigated for posts containing PPCs and those without through text mining methods and psycholinguistic analyses with LIWC. Specifically, the following research questions (RQs) were addressed, *i) What and how frequently can expressions of PPCs be observed among members of the subreddit, ii) What sentiments and emotional tone are associated with posts including expressions of PPCs compared to those without,* and *iii) Do posts using natural textual expressions of PPCs in the subreddit show significantly higher scores on textual markers of PTG than posts without PPC expressions?*

Methods

Study Design and Participants

This study utilised text mining procedures and linguistic analyses with LIWC to investigate expressions of PPCs and PTG on a large corpus of recent postings in a trauma-related forum on Reddit. Publicly available data were collected from the *r/traumatoolbox* subreddit by scraping threads and comments posted between February 2023 and February 2024. Only postings from members who contributed to discussions on the subreddit's most upvoted threads during that period were included, excluding Reddit moderators and chatbots. Ethical approval for this study was granted by the Faculty of Behavioural, Management and Social Sciences ethics committee of the University of Twente (No. 240116).

Setting

The subreddit *r/traumatoolbox* is an online forum intended for those who “seek or share coping strategies, resources, […], and other survivor tools” (Reddit.com, 2013). It was studied via text mining methods once before for user reactions to sexual abuse disclosure within the qualitative study by Andalibi et al. (2018). Since the study by Andalibi et al. (2018), the *r/traumatoolbox* subreddit grew from 372 subscribers in 2018 to over 23,000 members as of February 2024 and the subreddit is currently ranked among the top five percent by size within Reddit. Due to the community’s constant growth and active regular engagement among members for over five years, it was considered a fruitful platform for meaningful data collection.

PPCs and Related Terms

Due to the broadness of the positive psychology field, the selected theories and models are not exhaustive. PPCs (e.g., key terms like *hope* or *love*) derive from these models and were further investigated for their unique expressions and use of related terms in the forum. For this study, the following selection of positive psychological theories and models was chosen by the researcher to represent a broad spectrum of resulting PPCs.

The *ten pleasant emotions* by Fredrickson (2009) comprise *joy, gratitude, calm, interest, hope, pride, cheer, inspiration, awe,* and *love.* Emotions like pride, inspiration or interest are associated with growth and feelings of overcoming challenges, while gratitude, awe, and love are connected to rather social, even spiritual concepts (Bohlmeijer & Hulsbergen, 2018). Fredrickson’s model of ten pleasant emotions contributes a way of exploring the use of pleasant emotions in text.

The *Values in Action* (*VIA*) *Character Strengths* were developed by Peterson and Seligman (2004) and comprise 24 character strengths which make up six virtues. The strength-based and non-pathologising taxonomy became a brandmark for positive psychology and is regularly encouraged to be used in addition to rather pathologising clinical diagnostic manuals (Bannink, 2012). Character strengths constitute a core concept as its use is an essential part of positive psychology in practice and academic research, developed by one of positive psychology’s key founders, Martin Seligman (Littman-Ovadia et al., 2021). The VIA Character

Strengths were selected for their massive impact on the field and representation of a positive personality dimension.

The *PERMA model* (Seligman, 2011) comprises an acronym for *positive emotions*, *engagement*, *(positive) relationships*, *meaning*, and *accomplishment*. These five concepts are thought to represent the essential determinants of (subjective) well-being (Seligman, 2018) and were included to provide a concise model for understanding happiness and well-being.

The *self-determination theory* (Deci & Ryan, 2008) describes the drive towards *self-determination,* a state of personal growth and psychological freedom, by satisfying the three essential human needs *autonomy*, *competence,* and *relatedness*. These needs are best fulfilled and simultaneously reinforced through intrinsic *motivation* (Deci & Ryan, 2008). Self-determination theory represents a profoundly influential theory in positive psychology because of its focus on optimal human functioning (Bohlmeijer & Hulsbergen, 2018) and contributes a way to explore human motivation and needs for personal growth.

Compassion and *self-compassion* have been extensively studied, among others, by Paul Gilbert (2020) and Kristin Neff (2011). These concepts play a crucial role in trauma recovery and therapy (Maté, 2012; Paul Gilbert, 2020). Compassion has evolved through evolutionary processes and constitutes not only an emotion but also a survival motivational system (Gilbert, 2020). Both concepts are considered fundamental in positive psychology (Cassell, 2009).

Resilience (Bonanno et al., 2011) denotes the ability, either as a state or trait, to effectively recover from adverse situations. It is frequently associated with PTG (Clay et al., 2009; Vieselmeyer et al., 2017), and constitutes a long-studied core concept in positive psychology (Bohlmeijer & Hulsbergen, 2018; Cohn et al., 2009)

The PTGI, developed by Tedeschi and Calhoun (1996), is the gold standard assessment scale of PTG. As introduced before, it comprises the five dimensions of *new possibilities, relating to others, personal strength, spiritual change,* and *appreciation of life* (Tedeschi & Calhoun, 1996) and provides a highly researched indication of concepts contributing to PTG.

The total selected PPCs amount to 60. However, gratitude, love, and hope are represented by more than one theory and thus 57 unique PPCs remain. The full list of selected theories, models, and respective PPCs can be found in Appendix A. Opposed to the predefined PPCs, their related terms emerged from the natural language of posts based on the following inclusion criteria.

Related terms (or expressions of PPCs) were defined as any word sharing the main word stem or conjugation of a PPC (e.g., *joy**, *hop*, forgiv**). This includes nominalisations (e.g., *pride; proudness, proudly*) and other morphological variations such as misspellings when containing the word stem or differences between American and British English. To further qualify as a related term and to avoid misrepresentations (e.g., *awe* and *drawer*), a conceptual relation to the original PPC was required. This was done through deductive evaluations by the researcher (i.e., reading each possibly related term from the output and deciding whether they are conceptually related). Additionally, synonymous words and their stems were included as further representations of PPCs when they emerged from the data and were clearly related to the selected PPCs or constituted a common expression of a PPC in the forum.

Data Sources and Text Processing

A text mining approach was employed to explore natural expressions in forum posts. Text mining is the automated process of analysing unstructured textual data by translating text into analysable information using NLP and machine learning protocols (Zhang et al., 2015). The use of these algorithms enables quick text-extraction, processing and visualisation of latent textual information such as frequencies of words or sentiments conveyed in posts (Zhang et al., 2015). A general pipeline for text mining includes text pre-processing (collection and cleaning of the textual data), text mining operations (algorithm-driven operations aiming to uncover latent information via feature extractions), and post-processing (altering the data for visualisation or interpretation purposes; Zhang et al., 2015). Despite the automated procedures, text mining remains an interactive and iterative process and analysis settings must be adapted repetitively for optimal outcomes (Yu et al., 2014; Kononova et al., 2021). Modern transformer-based models and psycholinguistic programs like LIWC can manage most pre-processing steps automatically.

LIWC is a software developed by Francis and Pennebaker (1992) to analyse psycholinguistic features and count word frequencies of unstructured textual data. Using hierarchically structured dictionaries, LIWC can perform a range of linguistic analyses and text analysis tasks to assess and compare the linguistic contents and style of text as in forum posts. LIWC's primary analysis (called *LIWC Analysis*) uses a set of more than 30 included dictionaries with over 12,000 respective words to analyse natural expressions in over 80 concepts and themes. Using these dictionaries, LIWC can analyse complex psycholinguistic features such as cognitive processes, emotion, and tone expressed in text (Pennebaker et al., 2022). LIWC and the

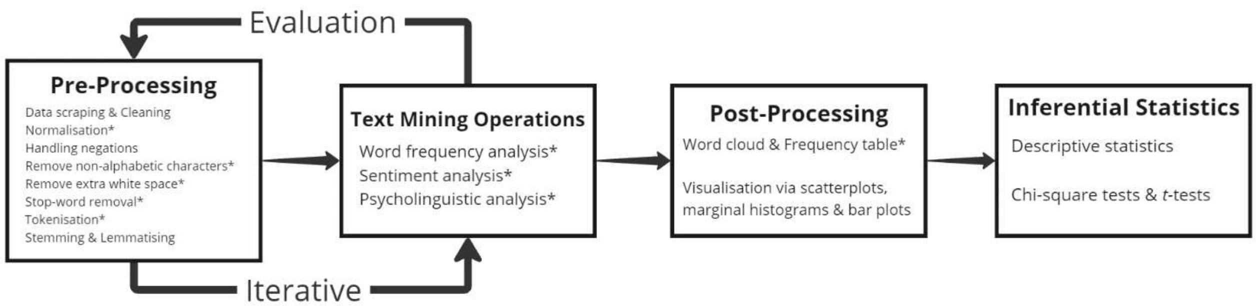
LIWC Analysis have been extensively used and validated in years of academic research (Pennebaker et al., 2022). The LIWC Analysis may detect indications of PTG in text through high scores on PTG-relevant constructs like *cognition* as previously done in other studies (e.g., Zheng et al., 2019). Moreover, it can assess emotion words and tone conveyed in posts which informs about the subjective context. These markers are preliminary though, in that there is no consistent validation of textual markers for PTG across different studies and populations (Mathews, 2019).

Data Analysis and Inferential Statistics

Following guidelines of Zhang et al. (2015), the posts were processed after the general text mining pipeline including text pre-processing, text-mining operations, and post-processing. Subsequently, inferential statistics were computed to test for differences between groups of posts. A flowchart depicting the study-specific text mining pipeline is presented in Figure 1.

Figure 1

Study-Specific Text Mining Pipeline



Note. ‘*’: Can be processed automatically with Linguistic Inquiry and Word Count.

Pre-Processing

Pre-processing of the data was done following open vocabulary procedures as suggested by Hickman et al. (2020). Open vocabulary approaches are used when extracting emergent features from the text for further use in subsequent analyses. In contrast, closed vocabulary approaches utilise predefined labels (like PPCs) and dictionaries to analyse text. This study employed a mixed approach to count preselected words and identify emergent related terms from text, which necessitates open vocabulary procedures (Hickman et al., 2020). The pre-processing for open vocabulary approaches according to Hickman et al. (2020) includes converting capital letters to lowercase (*normalisation*), handling negation words (*negations*; such as no, don’t, never), correcting spelling errors, expanding contractions & abbreviations, removing punctuation and non-meaningful expressions (*stop word removal*), separation of units of words (n-grams) from text (*tokenization*), reduction of words to their base stem (*stemming*), and finding meaningful variations of words and word stems (e.g., conjugations; *lemmatisation*).

Data Scraping and Cleaning. The data corpus of this study comprised a selection of 1,000 publicly available threads and 4,519 comments from 1,236 members posted on the subreddit *r/traumatoolbox*. Inclusion criteria constituted threads and comments published in the one-year period with the highest user engagement rated by upvotes of threads. Since the Reddit API limits the maximum number of scraped threads to 1,000, this limit was adhered to, as suggested by Andalibi et al. (2018). The posts were scraped via the statistical software *R* version 4.3.2 (R Core Team, 2023) and the *R* package *RedditExtractoR* version 3.0.9 (Rivera, 2023). Threads containing only a title or no natural text (i.e., weblinks only) were deleted. Furthermore, comments being marked as removed, deleted, or written by the subreddit's moderators as announcements or reminders were excluded. The resulting threads and comments were merged into one dataset.

Open Vocabulary Processing. With R, all letters in posts were converted to lowercase. Spelling errors and abbreviations were not corrected due to the diverse formulations of posts. Negations were assessed using 23 predefined words in the *negation.words* dictionary from the R package *qdapDictionaries* (Rinker, 2018) including *no, not, don't, never, neither, nor, nobody,* and 16 more. Traditionally, words are counted as negated when a negation is placed right before a word of interest, which cannot account for negations further away than one place in a phrase though (e.g., *I do not like optimism*). Here, negations were estimated by filtering posts which contained both PPCs and negation words. PPCs were considered negated if they co-occur within a three-word span of any negation word using R and were subsequently indicated as such in the output. This was reasoned to include negations which do not stand directly before a PPC. All non-alphabetic characters were removed such as smileys, numbers, special characters and punctuation, as well as extra white spaces or any word containing the string *https* to avoid weblinks. Stop word removal was conducted by using the stop word list provided by the *tm* R package (version 0.7-11; Feinerer, 2023) and LIWC's integrated stop word list in the Word Frequencies analysis (LIWC-22 version 1.8.0; Pennebaker et al., 2022). Tokenisation was done automatically with LIWC. Stemming and lemmatising were part of the research design and performed by filtering the tokenised output after the afore-described inclusion criteria for related terms using R.

Text Mining Operations

Word Frequencies of PPCs and Related Terms. To examine absolute frequencies of PPCs expressed within the data, LIWC's *Word Frequencies analysis* (Tausczik & Pennebaker, 2010) was used. LIWC's Word Frequencies analysis allows for the inspection of frequency descriptives of PPCs in posts by treating each one, two, or *n* words (n-grams) in posts as a separate unit and counting them. The pre-processed dataset was analysed with uni-, bi-, and trigrams, without omitting any n-grams or skipping texts. Higher n-grams than trigrams yield little extra information due to their low occurrence (Hickman et al., 2020; Kern et al., 2016). The subsequent output of tokens was filtered for preselected PPCs (e.g., *joy*, *hope, forgiveness*) and related terms. In the case of PPCs consisting of three words and using a preposition as in *love of learning* or *appreciation of beauty* the trigrams were further subdivided into bigrams such as *love learning* or unigrams of their main word stem like *learn** or *love**. That was done since prepositions like *of* will be filtered out by the stop word removal. Moreover, every bigram is seen as two unigrams by LIWC's Word Frequencies analysis and thus counted double. To avoid this overrepresentation a count was reduced from for instance the unigram *love* every time a bigram with love was counted. Relative word frequencies of each PPC and their negations were computed in addition to LIWC's statistics with R.

Examining Sentiments and Emotional Tone of Posts. To examine *sentiments* and *emotional tone*, the R package *SentimentAnalysis* (version 1.3-5; Proellochs & Feuerriegel, 2023) and LIWC were used. The posts were divided into two subgroups with one group containing at least one PPC or related term, and the other mentioning no such terms, to compare their sentiments. For each of the three groups (all posts; posts containing PPC expressions; posts containing no PPC expressions), sentiment analyses were conducted. Sentiment analyses can explore subjectivity by extracting negative, neutral, and positive sentiments from large corpora of texts like those produced by social media. For instance, lexicon-based sentiment analyses evaluate text based on priority-weighted positive and negative words from pre-assigned values in sentiment dictionaries (Bhardwaj et al., 2015; Nandwani & Verma, 2021; Zhang et al., 2015). These sentiment dictionaries are used in software such as LIWC or can be accessed with R packages. The R package *SentimentAnalysis* contains four sentiment dictionaries including the

English Harvard-IV General Inquirer sentiment dictionary (SentimentGI) and the Quantitative Discourse Analysis Package sentiment dictionary (SentimentQDAP; Kim, 2021). Compared to the other two integrated dictionaries, which were intended for marketing purposes and analysing financial jargon, SentimentGI and SentimentQDAP were designed for more general applications (Kim, 2021). Both dictionaries rank positively and negatively connotated words and phrases on a continuous spectrum from -1 to +1 (Nandwani & Verma, 2021) and accumulate these scores for each post. The two dictionaries can be employed with little cost, time, and effort while constituting reasonable sentiment analysis resources (Kim, 2021). Moreover, using more than one sentiment dictionary aligns with the recommendations of Czarnek and Stillwell (2022) in social media research, generating more reliable sentiments. The two dictionaries are described more specifically in the following two paragraphs.

SentimentGI. SentimentGI comprises 1,637 positive and 2,005 negative words derived from one of the most extensive text analysis dictionaries, the Harvard University's General Inquirer (Hurwitz, 2002; Kim, 2021). The word lists were developed by researchers from political and psychosocial fields (Crossley et al., 2016). After more than two decades since its emergence, the dictionary is still in widespread use and finds frequent integration in various text analysis programs such as in Sentiment Analysis and Social Cognition Engine (SÉANCE; Crossley et al., 2016).

SentimentQDAP. The University of Pittsburgh's Qualitative Data Analysis Program (QDAP) dictionary combines a variety of dictionaries intended for general purposes as in social media monitoring, marketing, or psychological research (Kim, 2021). The SentimentQDAP is part of the QDAP dictionary and can identify 2,003 positive and 4,776 negative words for sentiment analyses. It contains a subset of the SentimentGI, but also additional words relevant to opinion mining in various fields such as politics (Rinker, 2018).

Furthermore, subjectivity can also be expressed via emotion words like *crying* or *happy*. LIWC’s dictionary (LIWC-22 Dictionary (English); Pennebaker et al., 2022) can detect those emotion words (called *emotion detection*; Nandwani & Verma, 2021), and construct a more nuanced assessment of emotional states measured separately in positive and negative valence. The current version of LIWC (LIWC-22; Pennebaker et al., 2022) includes 337 positive emotion words and 612 negative emotion words (Sametoğlu et al., 2023) and assesses psycholinguistic categories on a scale from 0 to 100. Here, emotional tone is separated into LIWC’s *tone* dimension (akin to sentiments) and *emotion words.* For many years, textual research has continuously refined and updated these dictionaries (Boyd et al., 2022; Pennebaker et al., 2022).

PPCs and Linguistic Markers of PTG. The third RQ was investigated using *LIWC Analysis* (Pennebaker et al., 2022). The posts containing PPC expressions and those without were compared for textual markers of PTG. To explore a broad set of concepts potentially related to PTG, 12 psycholinguistic dimensions and their 4 overarching categories *cognition*, *affect*, *social*, and *health* were selected from the LIWC-22 dictionary. LIWC hierarchically structures dictionaries from broad to specific concepts. That is, the overall category (e.g., social), is divided into subcategories like *social references*, and dimensions of subcategories like *family*-related words. However, overarching categories assess more words than just the sum of words in their subcategories and dimensions (Boyd et al., 2022). Moreover, negations are not considered in LIWC Analysis and the software solely rates the occurrence of terms. The following paragraphs briefly describe these categories and dimensions in LIWC Analysis according to Boyd et al. (2022) and provide the rationale for inclusion.

Cognitive Category. The cognitive category assesses how many words in a text are related to thinking and thought processes, like reflecting. It comprises three subcategories, of which one, cognitive processing (e.g., words like *know*), was reported to be a potential textual marker of PTG by moderation of meaning-making (Zheng et al., 2019). Specifically the *cause* (e.g., words like *consider*) and *insight* (e.g., words like *because* or *hence*) dimensions from the cognitive processing subcategory seem to show correlations with PTGI measures (Zheng et al., 2019). Thus, the *cognitive* category and its subcategories *cognitive processing*, *insight*, and *cause* were utilised to investigate differences in the subgroups.

Affect Category. Since the update to LIWC-22, the dictionary differentiates between affect, emotion, and tone. While the tone assesses a dimension similar to sentiments and captures positive and negative connotations of words such as *kill*, or *birthday*, the emotion category captures a broad range of emotion-specific words like *laughing* or *crying*. Beyond emotion, LIWC categorises *affect* as an overarching concept, describing the intensity and tendency to use any words related to emotion or sentiments. The most detailed affective dimensions in LIWC assess three of the six basic human emotions, *anxiety*, *anger*, and *sadness*. Since those three emotions have a resemblance to symptoms of PTSD (WHO, 2023), they have been included as measures along with the overall *affect* category. These subjective measures are frequently utilised in social media research and textual PTG studies (Park et al., 2018; Scrignaro et al., 2017).

Social Category. Social categories like *social references* (including words like *he*, *she*, or *relationship*) are used to estimate how much the text focuses on social networks. Moreover, the two dimensions of *family* and *friend* within the social references subcategory evaluate words which are specifically referring to these social groups. The overarching *social* category assesses how many words in text are related to any social aspects. The inhibiting influence of social support on PTSD development has long been acknowledged (Brewin et al., 2000; Calhoun et al., 2022), and since some selected PPCs like *relatedness* are socially rooted, they might have an intersection with PTSD inhibition and potentially PTG. The dimensions *family* and *friend* from the subcategory *social references* and its superordinate social category have thus been included.

Health Measures. The distinction between dimensions of *illness, wellness*, and *mental* (health) in the *health* category was implemented with the latest LIWC version. The *illness* dimension describes words which relate specifically to physical symptoms and diseases, such as *headaches*. Similarly, the *mental* dimension focuses solely on psychological symptoms and pathologies such as *depression* or *suicide*. The *wellness* dimension, in contrast, captures activities and behaviours which represent vitality like *yoga* or *exercise*. The *health* category, a subcategory of overarching physical measures, captures terms generally related to health, whether of pathological or healthy nature. *Illness, wellness, mental*, and their superordinate category *health* represent textual measures of psychological and physiological health concernedness in the text and were thus selected.

Post-Processing

Post-processing was done by providing a word frequency table for every positive psychological theory or model and a word cloud with the 50 most frequently used words in the forum. Sentiments of posts were displayed using scatterplots with marginal histograms. Bar plots were utilised to visualise comparisons between scores of subgroups on LIWC categories and dimensions. Descriptive statistics of analysis results were provided in tables for each dictionary.

Inferential Statistics

The two groups of posts with and without PPCs or related terms were compared along their sentiment scores, tone, emotion, and 12 LIWC Analysis dimensions with their four overarching categories. Descriptive statistics were computed using R. Outliers were calculated and indicated as such when scoring at least three standard deviations away from the mean. Group mean differences in sentiment and LIWC Analysis scores were tested by two-sample *t*-tests. To investigate the relation between sentiment distributions and subgroups, chi-square tests of independence were conducted.

Results

Descriptive Data

A total of 940 threads with 3,377 comments posted by 1,234 unique forum members remained after pre-processing. The accumulated 4,317 posts showed an average length of 133 words per post (min = 1, max = 4,825). The total words before stop word removal amounted to 576,035 with 20,595 unique words. After stop word removal, 175,379 total words and 14,980 unique words were retained.

Frequencies of PPC Expressions

To examine *what and how frequently expressions of PPCs can be observed among members of the subreddit*, LIWC's Word Frequencies Analysis (Pennebaker et al., 2022) was utilised. A variety of natural expressions emerged from the forum members' posts. In addition to the 57 preselected PPCs, 194 related terms were identified based on inclusion criteria, with two being bigrams (i.e. *love learn* from *love of learning* and *positive relationship* from *positive relationships*) and the rest being unigrams. Only one trigram, the PPC *post traumatic growth*, was identified as meaningful in the posts. Unique expressions like *lovebombing* from *love* were rare, and most related terms constituted conjugations. However, three common expressions emerged and were considered additional relevant word stems in the related terms. Those comprise the speech-act *thank** for gratitude, *relig** as embodiment of spirituality, and *friend** as a representation of positive relationships. In fact, *thank*, *friend, friends, relationship, love* and *hope* were among the 50 most commonly used terms in the one-year period after stop-word removal. Figure 2 presents a word cloud highlighting the 50 most frequently expressed words in the forum's most upvoted posts after stop word removal, with PPCs and related terms highlighted in green.

Figure 2

Word Cloud of the 50 Most Frequently Used Words in the Subreddit's Most Engaged Posts After Stop Word Removal Between February 2023 and February 2024

Note. The size and transparency of words in the word cloud emphasise frequency differences. PPC expressions are highlighted in green.

Not surprisingly, *trauma* was ranked first with 1719 counts in the trauma-related forum. With respect to PPCs, the term *thank* from gratitude was observed most frequently from all PPC expressions with 621 counts ranking 14th of the most frequently used words. *Love* amounted to 532 counts ranked 26, followed by *friends* ranked 31 with 467 counts. Other concepts in the word cloud like dad, mom, mother, family, or parents may show conceptual relation to social PPCs such as *relatedness* or *relating to others.* However, due to the family's acknowledged role in trauma aetiology (Felitti et al., 1998), these terms were not considered representations of necessarily positive relationships.

Overall, the chosen words showed frequent occurrences in posts from forum members. The 251 PPC expressions amounted to 1.68% of the 14,980 unique words after stop-word removal. However, they were present in 59.78% of all investigated posts. The accumulated word frequencies of PPCs, frequency of negations, number of related terms from PPCs and their contribution to the total word count (k = 175,379) after stop word removal in percentage can be found in Tables 1 to 4 for each theory and model. The word stems *relat*, apprec*, spirit*, relig*, positiv** of related terms, as well as the PPCs *gratitude, hope,* and *love* were included in more than one theory or model and indicated as such with brackets in the output table to avoid misrepresentations. Extensive frequency tables of all preselected PPCs and identified related terms are provided in Appendix B.

Table 1

Accumulated Word and Negation Frequencies of PPC Expressions from Ten Pleasant Emotions (Fredrickson, 2009)

PPC	Expression Frequency	Negation Frequency	Related Terms	% of Total Words
gratitude	882	16	9	0.50
joy	166	7	7	0.09
hope	502	11	5	0.29
calm	150	3	6	0.09
interest	164	14	4	0.09
pride	9	0	2	0.01
cheer	5	1	3	0.00
inspiration	16	1	4	0.01
awe	28	0	1	0.02
love	787	54	12	0.45

Note. PPC = positive psychological concept.

Table 2

Accumulated Word and Negation Frequencies of PPC Expressions from Values in Action Character Strengths (Peterson & Seligman, 2004)

PPC	Expression Frequency	Negation Frequency	Related Terms	% of Total Words
wisdom	33	4	4	0.02
courage	64	3	5	0.04
humanity	4	0	0	0.00
citizenship	3	1	2	0.00
temperance	0	0	0	0.00
transcendence	1	0	1	0.00
creativity	22	0	2	0.01
curiosity	46	0	3	0.03
judgement	75	13	9	0.04
perspective	83	1	1	0.05

bravery	28	1	3	0.02
perseverance	2	0	2	0.00
zest	0	0	0	0.00
honesty	203	11	2	0.12
social-intelligence	139	9	5	0.08
kindness	41	1	4	0.02
(love)	787	54	12	0.45
leadership	125	6	6	0.07
fairness	73	15	2	0.04
teamwork	30	2	5	0.02
forgiveness	210	34	6	0.12
(love) of learning	1141	73	13	0.65
(gratitude)	882	16	9	0.50
spirituality	83	4	6	0.05
self-regulation	0	0	0	0.00
humility	2	0	0	0.00
appreciation of beauty	256	5	8	0.15
prudence	2	0	2	0.00
(hope)	502	11	5	0.29
humour	15	0	2	0.01

Note. PPC = positive psychological concept.

Table 3

Accumulated Word and Negation Frequencies of PPC Expressions from PERMA Model and Self-determination Theory

PPC	Expression Frequency	Negation Frequency	Related Terms	% of Total Words
		PERMA Model (Seligman, 2011)		

positive emotions	94	5	3	0.05
engagement	62	1	3	0.04
positive relationships	1851	79	18	1.06
meaning	49	3	1	0.03
accomplishment	25	3	5	0.01
Self-determination Theory (Deci & Ryan, 2008)				
self determination	0	0	0	0.00
determination	13	0	2	0.01
autonomy	7	0	2	0.00
competence	7	3	2	0.00
relatedness	661	31	7	0.38
motivation	19	1	1	0.01

Note. PPC = positive psychological concept.

Table 4

Accumulated Word and Negation Frequencies of PPC Expressions from Compassion and Self-compassion, Resilience, and PTGI

PPC	Expression Frequency	Negation Frequency	Related Terms	% of Total Words
Compassion and Self-Compassion (Gilbert, 2020; Neff, 2011)				
compassion	70	2	1	0.04
self compassion	2	0	0	0.00
Resilience (Bonanno et al., 2011)				
resilience	17	1	2	0.01
PTGI (Tedeschi & Calhoun, 1996)				
post traumatic growth	303	13	6	0.17
new possibilities	78	4	3	0.04

relating to others	661	31	7	0.38
personal strengths	47	0	3	0.03
spiritual change	83	4	7	0.05
appreciation of life	131	4	6	0.07

Note. PPC = positive psychological concept, PTGI = post-traumatic growth inventory.

Every theory or model was represented in the natural language in posts. Only the PPCs *temperament*, *zest* and *self-regulation* from the VIA Character Strengths did not occur in the posts themselves, nor were they linked to any meaningful related terms. Especially social PPCs such as *relatedness*, *relating to others*, or *positive relationships* and their related terms showed relatively high word counts across the different theories. Among all preselected concepts, *positive relationships* was most frequently expressed and showed a conceptual relation to 18 emerging related terms from the text, such as *friend* or *relation.* However, also emotion-based words around *gratitude, hope, joy,* and *love* occurred rather frequently compared to other PPCs.

Sentiment and Emotional Tone

To investigate *which sentiments and emotional tone are associated with posts containing expressions of PPCs compared to those without in the subreddit*, the 4,317 posts were divided based on their inclusion of at least one PPC expression, rendering 2,581 posts with PPCs or related terms and 1,736 posts without.

Sentiment Analysis

From the 2,003 positive words in the SentimentQDAP dictionary, 87 were shared with the selected 251 PPCs and emerging related terms. This was also the case for 73 of the 1,637 positive words in the SentimentGI dictionary. No PPC expression was shared with the negative word lists. Moreover, both dictionaries show similar distributions of negative and positive outliers (scores at least three standard deviations below and above the mean, respectively). Descriptive statistics of sentiment scores from all posts, posts containing PPC expressions, and posts without PPCs are presented in Table 5 for the two sentiment dictionaries in comparison.

Table 5

Frequencies and Descriptive Statistics of Sentiment Analysis Results with SentimentGI and SentimentQDAP

Posts	Descriptive Statistics					Frequencies in %		
	N	Mean Score	*SD*	Negative Outlier	Positive Outlier	Neutral Sentiment	Negative Sentiment	Positive Sentiment
				SentimentGI				
All	4,317	0.1	0.22	20	81	10.42	21.71	67.89
PPCs	2,581	0.14	0.21	1	61	5.19	16.28	78.52
No PPCs	1,736	0.05	0.23	33	34	18.22	29.77	52.01
				SentimentQDAP				
All	4,317	0.1	0.22	17	90	11.10	21.68	67.24
PPCs	2,581	0.14	0.21	0	65	5.11	16.97	77.92
No PPCs	1,736	0.05	0.23	28	39	19.99	28.69	51.32

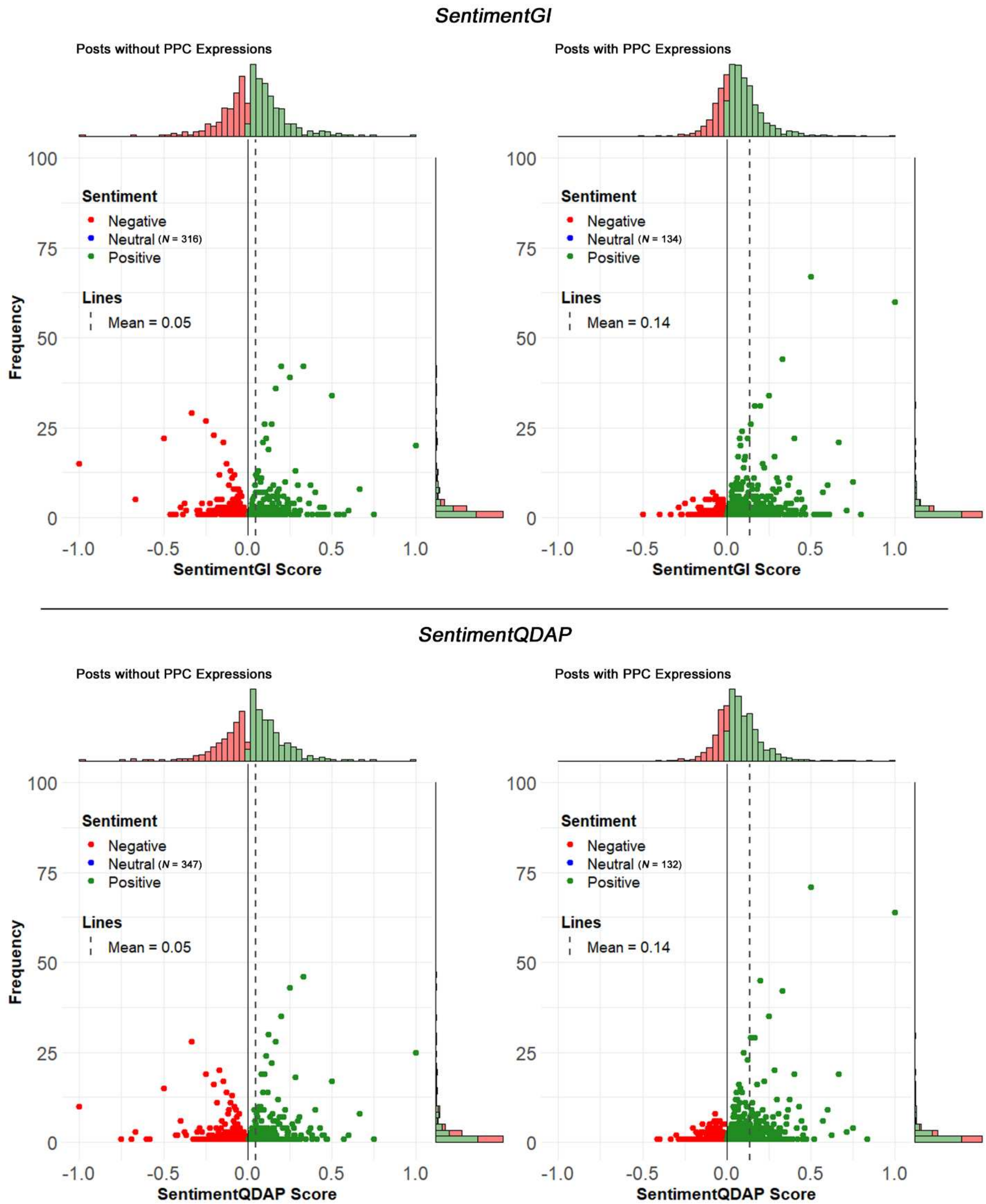
Note. PPCs = positive psychological concepts, SentimentGI = sentiment dictionary from Harvard's general inquirer, SentimentQDAP = sentiment dictionary from the Qualitative Data Analysis Program.

The two sentiment dictionaries in SentimentAnalysis showed very comparable sentiment scores with almost identical means and standard deviations after rounding to two decimals in all analyses. Moreover, most outliers expressed a positive sentiment, and all negative outliers derive from posts without PPC expressions, except one at -0.5 for SentimentGI.

Two-sample *t*-tests between posts containing PPCs and posts without showed that the former were rated significantly more positively than posts without PPCs by both dictionaries ($t_{\text{SentimentGI}}(3373) = 13.20$, $p < .001$; $t_{\text{SentimentQDAP}}(3436) = 13.07$, $p < .001$). Moreover, chi-square tests of independence were performed to investigate the relation between sentiment distributions and posts with and without PPC expressions. The relation between the variables was significant for both dictionaries ($X^2_{\text{SentimentGI}}(2, N = 4317) = 363.96$, $p < .001$; $X^2_{\text{SentimentQDAP}}(2, N = 4317) = 381.83$, $p < .001$), indicating that posts which include PPC expressions were more likely than posts without to be classified as positive. Figures 3 and 4 show scatterplots with marginal histograms comparing sentiment analysis results for SentimentGI and SentimentQDAP between subgroups and across all posts respectively.

Figure 3

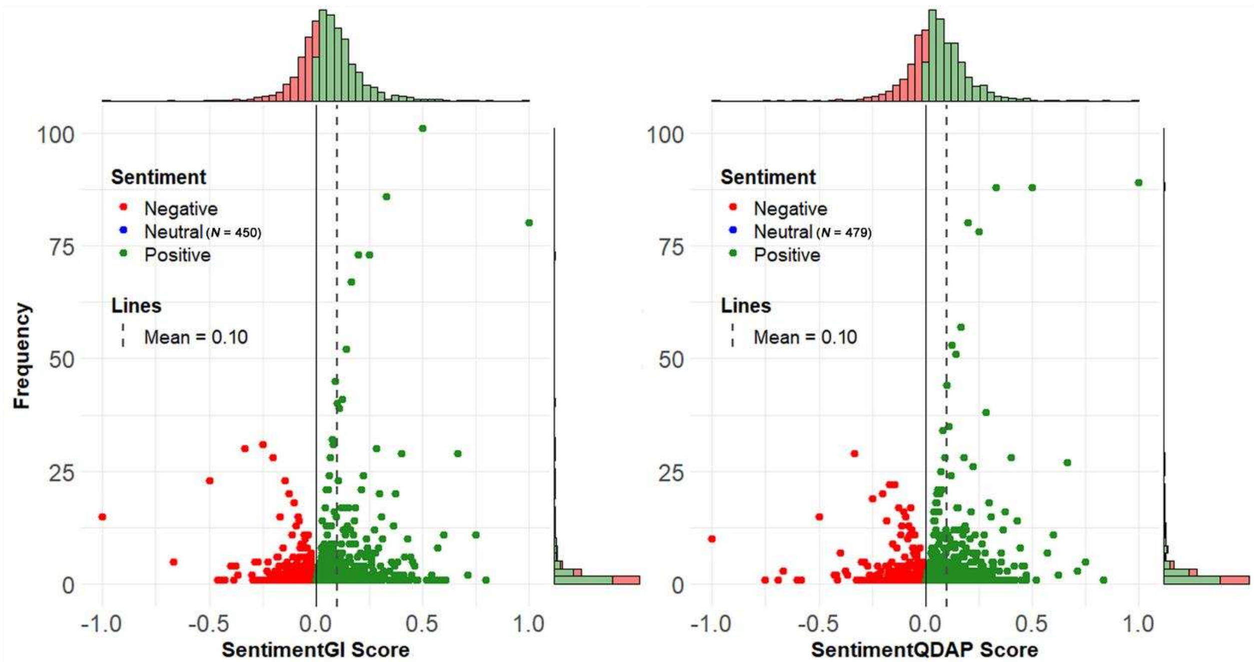
Scatterplots of Sentiment Scores from Post Subgroups with SentimentGI and SentimentQDAP



Note. PPC = positive psychological concept, SentimentGI = sentiment dictionary from Harvard's general inquirer, SentimentQDAP = sentiment dictionary from the Qualitative Data Analysis Program.

Figure 4

Scatterplots of Sentiment Scores of All Subreddit Posts with SentimentGI and SentimentQDAP



Note. SentimentGI = sentiment dictionary from Harvard's general inquirer, SentimentQDAP = sentiment dictionary from the Qualitative Data Analysis Program.

The overall sentiment scores from all analyses showed a tendency towards positive sentiment across all posts. An accumulation of posts around 0.5 can be observed in the PPC group, mostly due to two-word phrases containing a positively rated word like *thank* and a neutral word such as *you,* which results in a score of 0.50. Similarly, the extreme outliers at 1 comprised mostly positively connotated one-word comments like *thanks* or *beautiful.*

Emotion and Tone

Emotion words and conveyed tone were examined using dictionaries from the affect category in LIWC Analysis. LIWC assesses negative and positive valence separately for the two dimensions. Table 6 presents the descriptive statistics of the LIWC Analysis outcomes for tone and emotion words.

Table 6

Descriptive Statistics of LIWC Analysis Outcomes for Emotion and Tone Dimensions of All Posts and Subgroups

Posts	Negative				Positive			
	N_{Posts}	*M*	*SD*	Outlier	N_{Posts}	*M*	*SD*	Outlier
				Emotion				
All	2,530	1.75	2.69	74	1,938	1.18	3.15	83
PPCs	1,706	1.61	1.94	28	1,606	1.41	2.82	59
No PPCs	824	1.96	3.51	30	332	0.85	3.57	25
				Tone				
All	2,981	3.10	4.01	47	3,512	5.32	8.60	112
PPCs	1,940	2.84	2.65	25	2,474	6.44	9.54	295
No PPCs	1,041	3.49	5.41	26	1,038	3.65	6.65	34

Note. PPCs = positive psychological concepts.

The LIWC Analysis also indicated an overall positive-favouring tone. In PPC posts, the positive tone scores were more than twice as high as the negative scores. Words related to emotions like laughing or crying, however, tended towards higher negative than positive scores across all groups. Moreover, while negative and positive emotion scores were nearly balanced in PPC posts, posts without PPCs showed pronounced tendencies towards negative emotion scores. The two subgroups were significantly different in both tone ($t_{\text{ToneNegative}}(2297) = -4.64$, $p < .001$; $t_{\text{TonePositive}}(4310) = 11.31$, $p < .001$) and use of emotion words ($t_{\text{EmotionNegative}}(2459) = -3.78$, $p < .001$; $t_{\text{EmotionPositive}}(3124) = 5.47$, $p < .001$). That is, the positive tone and emotion were significantly higher, and the negative emotion and tone significantly lower, in posts containing PPCs or related terms compared to the posts without.

Linguistic Markers of PTG

To investigate *whether posts using natural textual expressions of PPCs in the subreddit show significantly higher scores on linguistic markers of PTG than posts without,* LIWC Analysis was leveraged using the cognitive, emotional, social, and health categories from the English LIWC-22 Dictionary. Descriptive statistics of the LIWC Analysis results for posts with and posts without PPC expressions in comparison are presented in Table 7.

Table 7

Descriptive Statistics of LIWC Analysis Categories for Posts with PPCs and Posts Without

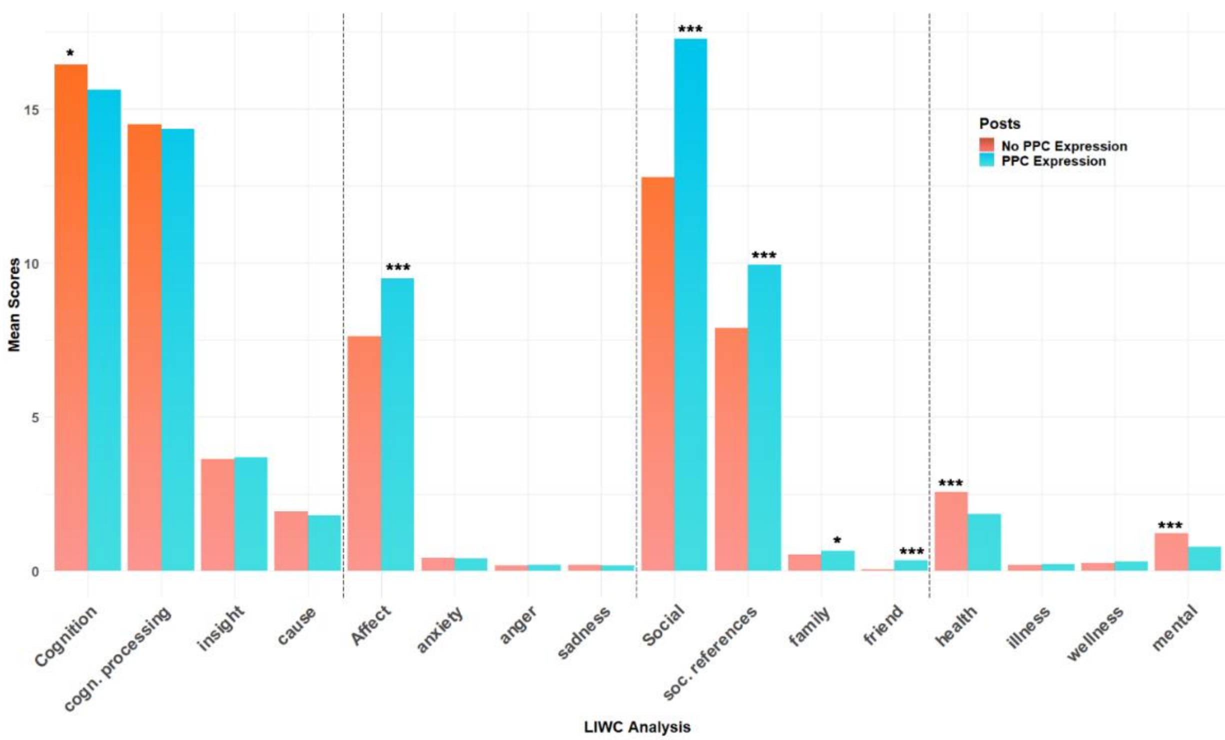
	Without PPC Expression $N = 1{,}736$				With PPC Expression $N = 2{,}581$			
Categories	N_{Posts}	*M*	*SD*	Outlier	N_{Posts}	*M*	*SD*	Outlier
Cognition	1,538	16.43	12.10	19	2,445	15.61	6.33	10
cogn. pro.	1,509	14.50	10.21	19	2,435	14.35	6.05	12
insight	1,114	3.62	4.73	27	2,169	3.69	2.97	34
cause	830	1.92	3.74	26	1,846	1.80	1.93	40
Affect	1,390	7.60	8.75	24	2,553	9.50	9.22	55
anxiety	307	0.42	1.32	31	869	0.41	0.99	43
anger	142	0.17	0.97	26	545	0.19	0.67	40
sadness	155	0.20	1.13	22	586	0.18	0.48	71
Social	1,508	12.77	10.32	21	2,564	17.27	13.55	65
soc. ref.	1,325	7.89	7.46	19	2,473	9.94	7.55	57
family	307	0.53	1.60	41	916	0.65	1.37	41
friend	25	0.04	0.51	11	619	0.35	1.41	28
health	834	2.55	4.96	24	1,705	1.84	2.42	38
illness	145	0.19	0.95	28	492	0.21	0.89	31
wellness	143	0.25	1.28	34	530	0.30	1.02	52
mental	538	1.23	3.18	26	1,188	0.79	1.45	50

Note. Superordinate categories are written in capital letters except *health*. N_{Posts} = number of posts containing words in category, LIWC = Linguistic Inquiry and Word Count, PPC = positive psychological concept, cogn. pro. = cognitive processing, soc. ref. = social references.

There was no significant difference between the groups for the three specific emotions. However, in terms of using overall affect words, the PPC group was significantly more likely than the non-PPC group to use words conveying any type of affect ($t_{Affect}(3850) = 6.83$, p < .001). Moreover, posts without PPCs used words concerning symptoms and pathologies in mental health, and health words generally, significantly more frequently than the PPC group ($t_{mental}(2223) = -5.43$, p < .001; $t_{health}(2297) = -5.52$, p < .001). For the overall cognition category, posts without PPC expressions were significantly more likely than the PPC group to use cognition words ($t_{\text{Cognition}}(2379) = -2.57$, p = .010), however, not for its dimensions. Especially the social category yielded contrasting results between the two subgroups. The LIWC Analysis showed a clear tendency for posts containing PPC expressions to include more social terms than posts without in all categories. While 86.83% of the posts without PPC expression contained words from the social category, 99.34% of the PPC group posted social words. Moreover, 1.44% of the posts referred to friends in the former group, while 23.98% of the PPC posts used words related to friends. The *t*-tests were significant for the social category and all subdimensions ($t_{\text{Social}}(4250) = 12.36$, $p < .001$; $t_{\text{socialreferences}}(3751) = 8.83$, $p < .001$; $t_{\text{family}}(3330) = 2.49$, $p = .013$; $t_{\text{friend}}(3500) = 10.17$, $p < .001$). A bar plot comparing posts with PPC expression and posts without on the 12 dimensions and four categories from LIWC Analysis is presented in Figure 5.

Figure 5

Bar Plot of Comparison Between Posts with PPC Expressions and Posts Without on 12 Dimensions and Four Categories from LIWC Analysis



Note. Significance level: '*' p < .05, '**' p < .01, '***' p < .001. Superordinate categories are written in capital letters except *health*. LIWC = Linguistic Inquiry and Word Count, PPC = positive psychological concept, cogn. processing = cognitive processing, soc. references = social references.

Discussion

This study aimed to explore textual expressions of PPCs and PTG in the subreddit *r/traumatoolbox* using text mining methods and the psycholinguistic software LIWC. The overall objective was to investigate how common positive psychological theories and models are naturally expressed in posts and how these posts perform on psycholinguistic markers of PTG compared to those without such expressions. By analysing 940 threads with the highest user engagement rated by upvotes and their 3,377 comments from 1,234 accounts posted between February 2023 and February 2024 several important findings surfaced.

The preselected PPCs were supplemented by 194 related terms emerging from the threads and comments of forum members, most of which comprised conjugations. The 251 total terms could be found in nearly 60% of all investigated posts. From all PPC expressions, *thank* from gratitude was the most frequently observed in the community, followed by *love* and *friends* which shared their place in the top 50 words used in the forum after stop word removal. Especially social PPCs occurred frequently in the subreddit, with *positive relationships* being the most expressed PPC when combined with its related terms. Moreover, the sentiment in posts with PPC expressions was overall more positive than in posts without. Despite the higher likelihood of positive tone and sentiment in posts with PPC expressions compared to those without, all groups primarily used emotion words with negative valence. A more detailed psycholinguistic analysis showed that posts with PPCs relate significantly more often to social terms as well as using overall more affect words than posts without PPC expressions. Despite the focus on well-being in positive psychology, the wellness dimension from LIWC's health measures showed no significant differences between groups. However, the PPC group was also less concerned with words related to mental health and health generally. Notably, terms relating to overall cognition were more prevalent in the group without PPCs, but there was no significant difference between groups in cognitive dimensions indicating markers of PTG in related studies.

Frequencies of PPCs and Related Terms in the Subreddit

The frequent occurrence of PPCs related to *gratitude*, *hope*, or *love* may be attributed to the natural language used in online communities. Expressing gratitude encourages members to contribute more often through a kind of interactive gratitude cycle (Makri & Turner, 2020). Moreover, peer communication in mental health forums often involves high levels of disclosure and support-seeking (Andalibi et al., 2018), which can stimulate grateful responses and hopeful feelings (Morrow, 2016; Park et al., 2018). Given the subreddit's focus on sharing trauma coping strategies for those who seek support (Reddit.com, 2013) and the occurrence of the word *support* in the top 50 words, support-seeking might play a significant role in the forum's most upvoted threads as well. Other text mining studies using LDA topic modelling found similar support-seeking indications in trauma-related mental health subreddits, such as frequent use of the word *help* and the *seeking advice* topic in *r/ptsd* (Low et al., 2020). Another study by Park et al. (2018) affirmed that gratitude and positive emotions are common responses to support-seeking behaviour on mental health subreddits. They investigated *r/anxiety*, *r/depression* and *r/ptsd* for thematic differences using *k*-means clustering and found that the PPCs *positive emotion* (including *hope* and *love*) and *gratitude* emerged as common topics across all three subreddits. Moreover, topics related to sociality and support-seeking like *talking to friend* or *friends and family* were among the most communicated concepts and linked with grateful responses (Park et al., 2018). This study supports Park et al.'s (2018) findings, showing that social PPCs, and positive emotions like love, hope, and gratitude were among the most expressed concepts in highly engaged posts within *r/traumatoolbox*. Despite differences in language use between subreddits (Gkotsis et al., 2016; Park et al., 2018), these core concepts of positive psychology appear to be key themes in trauma-related and also other mental health subreddits. Support-seeking tendencies of members in coping-focused mental health forums might explain the frequent occurrence of gratitude and positive emotions in the forum. Future research could investigate more closely whether expressions of these PPCs are relevant factors for experiencing PTG in trauma-related online communities, and whether differences exist in how they are communicated in different subreddits. Those insights could inform the development of PTG fostering online environments.

Sentiments, Emotion and Tone Conveyed in the Forum

The sentiment of the most engaged posts in the subreddit showed overall positive tendencies. Other studies found similar results when analysing the content of posts in different mental health subreddits. Using the sentiment dictionary VADER, Kamarudin et al. (2021) found predominantly positive sentiments in subreddits concerning *social anxiety, OCD, grief support,* and *depression.* Only subforums around *abuse* showed overall negative sentiment scores. Those findings show that the communication in most mental health subreddits conveys positive sentiments, and the current study adds *r/traumatoolbox* to this list with respect to the most engaged posts. Moreover, LIWC's indication of predominantly negative emotion words in the investigated posts surprisingly aligns with recent findings of research on mental health subreddits. Kim et al. (2023) investigated seven major mental health subreddits with LIWC for differences in the use of emotion words and found consistently negative tendencies in all, except *r/autism*. The study by Scrignaro et al. (2017) replicates these tendencies also in expressive writings. Using an earlier version of LIWC, they found a slightly more positive, but comparable positive-to-negative ratio like the current study in 25 PTG narratives of cancer patients ($M_{\text{negative}} = 10.55$, $SD = 12.09$; $M_{\text{positive}} = 8.65$, $SD = 6.51$). In light of these results, the posts in the subreddit show a common pattern in sentiment distribution and emotion word usage, consistent with trauma-related studies and other mental health subreddits. It could be that the high occurrence of negative emotion words like *crying,* or *sad* in combination with positive tone and sentiments hints at emotional disclosure and reports of negative feelings in an eventually supporting environment, creating a positive atmosphere for such disclosure. The difference in valence between emotion words and sentiments across studies affirms that the two affect dimensions do not necessarily reflect the same concepts and should be viewed as related, but separate constructs.

Furthermore, simple one- and two-word phrases like *thanks* or *thank you* were common in the posts and could have influenced the sensitive analyses. Due to the nature of online forums, some posts contain short responses to contributions, often in speech acts like *thanks.* In lexicon-based sentiment analyses, these brief comments are identified as outliers (if positive or negative) or neutral (if not evaluated), potentially skewing the analyses (Czarnek & Stillwell, 2022). However, for analysing the representation of PPCs, a short *thanks* may validly express gratitude, justifying the retention of these outliers in the analysis. Additionally, the two sentiment dictionaries showed similar means and standard deviations when rounded to two decimals. Other research on online customer reviews reported similar convergence between the dictionaries (Kim, 2021). The overlap of SentimentQDAP with SentimentGI (Rinker, 2018) might capture most words used in the forum. Academics may therefore benefit from using simpler, less extensive word lists. Ideally, dictionaries specific to forums would capture the subreddit-dependent language, slang, smileys, and other rather unique expressions (Gkotsis et al., 2016). For general sentiment analysis, a more concise dictionary like SentimentGI might suffice, saving resources, time, and effort while still providing reliable results.

Psycholinguistic Markers and Textual Dimensions of PTG on Reddit

Contrary to expectations and previous research on PTG, cognitive dimensions in posts with PPC expressions were significantly less pronounced than in those without. It could be that the use of PPC expressions does not influence textual indications of PTG in posts on Reddit. However, Mathews (2019) supports this study's findings, showing that cognitive expressions are not necessarily related to PTG in traumatised students. In the frame of her dissertation, Mathews (2019) found that the cognitive dimension derived from LIWC correlated with PTSD symptoms rather than PTG. She suggested that differences in trauma types, such as interpersonal (e.g., sexual assault) versus non-interpersonal (e.g., unexpected deaths), as well as the studied population might account for this. Additionally, using cognitive words might indicate avoidance behaviour through rationalisation instead of emotional processing (Mathews, 2019). Building on Mathews' (2019) reasoning, lower scores in the cognitive category of PPC posts could be related to the diversity of the subreddit's population. Reddit profiles are anonymous and age, location, or trauma-affected status cannot be retrieved. Moreover, most Reddit users are estimated to be young, high socioeconomic-status males (Proferes et al., 2021). These demographic uncertainties obscure which type of users are trauma-affected and capable of experiencing PTG. Growth after trauma may therefore be evaluated and facilitated differently in social media contexts compared to real-life settings and expressive writings of reportedly traumatised individuals. The contrasting results between studies on cognition words as textual markers of PTG highlight a significant opportunity for future research. Understanding how to support PTG development for specific populations through different channels could help create tailored PTG interventions.

Furthermore, the social category played a key role across all analyses. The prominence of social PPCs like *relationship, friend,* or *social* in the coping-focused forum corroborates with findings in PTSD and PTG research (e.g., Brewin et al., 2000; Calhoun et al., 2022; Tedeschi & Calhoun, 1995). Social support is a major protective factor against PTSD (Brewin et al., 2000) and aids in recovery, regardless of the type of relationship (e.g., spouse or friend), or kind of trauma experienced (Calhoun et al., 2022). Following Calhoun et al.'s (2022) biopsychosocial model, which asserts that trauma recovery is a biological, social, and psychological process, social factors might be at least as relevant in trauma recovery as psychological ones. That might especially be the case for major mental health subreddits, which show consistent relation to social topics and high scores on LIWC's social categories (Kim et al., 2023; Park et al., 2018), as replicated in this study for the posts with most upvotes. However, previous research assumed cognitive words to represent PTG through meaning-making (Mathews, 2019; Park, 2010; Zheng et al., 2019). Investigating PTG textually through terms related to social connectedness and relatedness could therefore uncover a new dimension particularly relevant in online mental health communities. Within these diverse populations, where anonymity protects the user's identity, the common ground might be the human need for relatedness (Deci & Ryan, 2008), support-seeking, and disclosure (Andalibi et al., 2018; Park et al., 2018). Online forums foster sociality and can provide social support, which may be why many individuals engage with them in the first place. The resulting sense of connectedness with others who share their experiences (Liao Siling et al., 2021) and positive emotions associated with sociality (Park et al., 2018) might be especially relevant in fostering PTG in digital mental health communities.

Limitations

The study had several key limitations. Demographic uncertainties were introduced due to anonymous Reddit profiles and the trauma-affected status of users was unknown. The study design allowed for a close inspection of one specific subreddit and its most upvoted threads and comments over a one-year period which limited generalisability. Selection bias may have been introduced in the selection of theories and models, integration of related terms, and choosing psycholinguistic categories. Lastly, satire and emojis have not been considered.

Conclusion

Textual mental health research on growth after trauma in social media remains limited. This study advances the field of positive psychology and PTG research as one of the first investigating a major trauma-related online forum on textual markers of PTG and presence of PPC expressions. The findings indicate frequent occurrences of positive emotional expressions around gratitude, love, hope, but especially social words like relationship. Moreover, posts containing PPC expressions conveyed more positive sentiment and used fewer negative emotion words than posts without. Introducing a social dimension as a textual marker of PTG in online forums could offer a valuable tool to evaluate how individuals may foster PTG in digital contexts on Reddit.

References

Alloghani, M., Al-Jumeily, D., Mustafina, J., Hussain, A., & Aljaaf, A. J. (2019). A systematic review on supervised and unsupervised machine learning algorithms for data science. *Unsupervised and Semi-Supervised Learning*, 3–21. https://doi.org/10.1007/978-3-030-22475-2_1

American Psychological Association. (2018, April 19). *APA Dictionary of Psychology*. American Psychological Association. https://dictionary.apa.org/trauma

Andalibi, N., Haimson, O. L., Choudhury, M. D., & Forte, A. (2018). Social support, reciprocity, and anonymity in responses to sexual abuse disclosures on social media. *ACM Transactions on Computer-Human Interaction*, *25*(5), 1–35. https://doi.org/10.1145/3234942

Bannink, F. (2012). *Practicing positive CBT: from reducing distress to building success*. John Wiley & Sons.

Beasley, A., & Mason, W. (2015). Emotional states vs. emotional words in social media. *Web Science*, *31*, 1–10. https://doi.org/10.1145/2786451.2786473

Bhardwaj, A., Narayan, Y., Vanraj, Pawan, & Dutta, M. (2015). Sentiment analysis for Indian stock market prediction using SENSEX and Nifty. *Procedia Computer Science*, *70*, 85–91. https://doi.org/10.1016/j.procs.2015.10.043

Bohlmeijer, E., & Hulsbergen, M. (2018). *Using positive psychology every day: learning how to flourish.* Routledge.

Bonanno, G. A., Westphal, M., & Mancini, A. D. (2011). Resilience to loss and potential trauma. *Annual Review of Clinical Psychology*, *7*(1), 511–535. https://doi.org/10.1146/annurev-clinpsy-032210-104526

Boyd, R. L., Ashokkumar, A., Seraj, S., & Pennebaker, J. W. (2022). *The Development and Psychometric Properties of LIWC-22*. University of Texas at Austin. https://doi.org/10.13140/RG.2.2.23890.43205

Brewin, C. R., Andrews, B., & Valentine, J. D. (2000). Meta-analysis of risk factors for posttraumatic stress disorder in trauma-exposed adults. *Journal of Consulting and Clinical Psychology*, *68*(5), 748–766. https://doi.org/10.1037/0022-006x.68.5.748

Calhoun, L. G., & Tedeschi, R. G. (2012). *Posttraumatic growth in clinical practice*. https://doi.org/10.4324/9780203629048

Calhoun, C. D., Stone, K. J., Cobb, A. R., Patterson, M. W., Danielson, C. K., & Bendezú, J. J. (2022). The role of social support in coping with psychological trauma: An integrated biopsychosocial model for posttraumatic stress recovery. *Psychiatric Quarterly*, *93*(4), 949–970. https://doi.org/10.1007/s11126-022-10003-w

Cassell, E. J. (2009). Compassion. *The Oxford Handbook of Positive Psychology*, 392–404. https://doi.org/10.1093/oxfordhb/9780195187243.013.0037

Cichosz, P. (2018). A case study in text mining of discussion forum posts: Classification with bag of words and global vectors. *International Journal of Applied Mathematics and Computer Science*, *28*(4), 787–801. https://doi.org/10.2478/amcs-2018-0060

Clay, R., Knibbs, J., & Joseph, S. (2009). Measurement of posttraumatic growth in young people: A review. *Clinical Child Psychology and Psychiatry*, *14*(3), 411–422. https://doi.org/10.1177/1359104509104049

Cohn, M. A., Fredrickson, B. L., Brown, S. L., Mikels, J. A., & Conway, A. M. (2009). Happiness unpacked: Positive emotions increase life satisfaction by building resilience. *Emotion*, *9*(3), 361–368. https://doi.org/10.1037/a0015952

Confino, D., Einav, M., & Margalit, M. (2023). Post-traumatic growth: The roles of the sense of entitlement, gratitude and hope. *International Journal of Applied Positive Psychology*, *8*(2), 453–465. https://doi.org/10.1007/s41042-023-00102-9

Crossley, S. A., Kyle, K., & McNamara, D. S. (2016). Sentiment analysis and social cognition engine (SEANCE): An automatic tool for sentiment, social cognition, and social-order analysis. *Behavior Research Methods*, *49*(3), 803–821. https://doi.org/10.3758/s13428-016-0743-z

Czarnek, G., & Stillwell, D. (2022). Two is better than one: Using a single emotion lexicon can lead to unreliable conclusions. *PLOS ONE*, *17*(10). https://doi.org/10.1371/journal.pone.0275910

Deci, E. L., & Ryan, R. M. (2008). Self-determination theory: A Macrotheory of human motivation, development, and health. *Canadian Psychology / Psychologie Canadienne*, *49*(3), 182–185. https://doi.org/10.1037/a0012801

Feinerer, I. (2023). tm: Text Mining Package. R package version 0.7-11. https://CRAN.R-project.org/package=tm

Felitti, V. J., Anda, R. F., Nordenberg, D., Williamson, D. F., Spitz, A. M., Edwards, V., Koss, M. P., & Marks, J. S. (1998). Relationship of childhood abuse and household dysfunction to many of the leading causes of death in adults. *American Journal of Preventive Medicine*, *14*(4), 245–258. https://doi.org/10.1016/s0749-3797(98)00017-8

Francis, M. E., & Pennebaker, J. W. (1992). Putting stress into words: The impact of writing on physiological, absentee, and self-reported emotional well-being measures. *American Journal of Health Promotion*, *6*(4), 280–287. https://doi.org/10.4278/0890-1171-6.4.280

Fredrickson, B. L. (2009). *Positivity*. New York: Three Rivers Press.

Gilbert, P. (2020). Compassion: From its evolution to a psychotherapy. *Frontiers in Psychology*, *11*. https://doi.org/10.3389/fpsyg.2020.586161

Gilo, T., Feigelman, W., & Levi-Belz, Y. (2020). Forgive but not forget: From self-forgiveness to posttraumatic growth among suicide-loss survivors. *Death Studies*, *46*(8), 1870–1879. https://doi.org/10.1080/07481187.2020.1864064

Gkotsis, G., Oellrich, A., Hubbard, T., Dobson, R., Liakata, M., Velupillai, S., & Dutta, R. (2016). The language of mental health problems in social media. *Proceedings of the Third Workshop on Computational Lingusitics and Clinical Psychology*. https://doi.org/10.18653/v1/w16-0307

Grant, R., Kucher, D., Leon, A. M., Gemmell, J., & Raicu, D. (2017). Discovery of informal topics from post traumatic stress disorder forums. *2017 IEEE International Conference on Data Mining Workshops (ICDMW)*. https://doi.org/10.1109/icdmw.2017.65

Hanley, T., Prescott, J., & Gomez, K. U. (2019). A systematic review exploring how young people use online forums for support around mental health issues. *Journal of Mental Health*, *28*(5), 566–576. https://doi.org/10.1080/09638237.2019.1630725

Hartmann, J., Huppertz, J., Schamp, C., & Heitmann, M. (2019). Comparing automated text classification methods. *International Journal of Research in Marketing*, *36*(1), 20–38. https://doi.org/10.1016/j.ijresmar.2018.09.009

Henson, C., Truchot, D., & Canevello, A. (2021). What promotes post traumatic growth? A systematic review. *European Journal of Trauma & Dissociation*, *5*(4), 100195. https://doi.org/10.1016/j.ejtd.2020.100195

Hickman, L., Thapa, S., Tay, L., Cao, M., & Srinivasan, P. (2020). Text preprocessing for text mining in organizational research: Review and recommendations. *Organizational Research Methods*, *25*(1), 114–146. https://doi.org/10.1177/1094428120971683

Holtz, P., Kronberger, N., & Wagner, W. (2012). Analyzing internet forums. *Journal of Media Psychology*, *24*(2), 55–66. https://doi.org/10.1027/1864-1105/a000062

Humphreys, A., & Wang, R. J. H. (2017). Automated text analysis for consumer research. *Journal of Consumer Research*, *44*(6), 1274–1306. https://doi.org/10.1093/jcr/ucx104

Hurwitz, R. (2002). *Descriptions of inquirer categories and use of inquirer dictionaries*. General Inquirer Categories. https://inquirer.sites.fas.harvard.edu/homecat.htm

Kamarudin, S. N., Beigi, G., & Liu, H. (2021). A study on mental health discussion through reddit. *2021 International Conference on Software Engineering & Computer Systems and 4th International Conference on Computational Science and Information Management (ICSECS-ICOCSIM)*, 637–643. https://doi.org/10.1109/icsecs52883.2021.00122

Kern, M. L., Park, G., Eichstaedt, J. C., Schwartz, H. A., Sap, M., Smith, L. K., & Ungar, L. H. (2016). Gaining insights from social media language: Methodologies and challenges. *Psychological Methods*, *21*(4), 507–525. https://doi.org/10.1037/met0000091

Kerry, N., Chhabra, R., & Clifton, J. D. W. (2023). Being thankful for what you have: A systematic review of evidence for the effect of gratitude on life satisfaction. *Psychology Research and Behavior Management*, *16*, 4799–4816. https://doi.org/10.2147/PRBM.S372432

Kim, R. Y. (2021). Using online reviews for customer sentiment analysis. *IEEE Engineering Management Review*, *49*(4), 1–1. https://doi.org/10.1109/emr.2021.3103835

Kim, S., Cha, J., Kim, D., & Park, E. (2023). Understanding mental health issues in different subdomains of social networking services: Computational analysis of text-based reddit posts. *Journal of Medical Internet Research*, *25*(1), e49074. https://doi.org/10.2196/49074

Kononova, O., He, T., Huo, H., Trewartha, A., Olivetti, E. A., & Ceder, G. (2021). Opportunities and challenges of text mining in materials research. *iScience*, *24*(3), 102155. https://doi.org/10.1016/j.isci.2021.102155

Liao Siling, J., Truss, K., Philips, L., Eastwood, O., & Bendall, S. (2021). Young people's journeys of recovery from trauma: A qualitative study of narratives from internet forums.

Psychological Trauma: Theory, Research, Practice, and Policy, *13*(3), 293–301. https://doi.org/10.1037/tra0000990

Linley, A., Willars, J., Biswas-Deiner, R., Garcea, N., & Stairs, M. (2010). *The strengths book: Be confident, be successful and enjoy better relationships by realising the best of you*. CAPP Press.

Littman-Ovadia, H., Dubreuil, P., Meyers, M. C., & Freidlin, P. (2021). Editorial: Via character strengths: Theory, research and practice. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.653941

Low, D. M., Rumker, L., Talkar, T., Torous, J., Cecchi, G., & Ghosh, S. S. (2020). Natural language processing reveals vulnerable mental health support groups and heightened health anxiety on reddit during covid-19: Observational study. *Journal of Medical Internet Research*, *22*(10). https://doi.org/10.2196/22635

Makri, S., & Turner, S. (2020). "I can't express my thanks enough": The "gratitude cycle" in online communities. *Journal of the Association for Information Science and Technology*, *71*(5), 503–515. https://doi.org/10.1002/asi.24257

Maté, G. (2012). Addiction: Childhood trauma, stress and the biology of addiction. *Journal of Restorative Medicine, 1*(1), 56–63. https://doi.org/10.14200/jrm.2012.1.1005

Maté, G. (2018). *In the realm of hungry ghosts: Close encounters with addiction*. London Vermilion.

Mathews, S. L. (2019). *Meaning-making, psychological outcomes, and language use when describing traumatic events* (pp. 1–45) [PsyD]. https://etd.ohiolink.edu/acprod/odb_etd/ws/send_file/send?accession=xavier1558042915273947&disposition=inline

Morrow, P. R. (2006). Telling about problems and giving advice in an internet discussion forum: Some discourse features. *Discourse Studies*, *8*(4), 531–548. https://doi.org/10.1177/1461445606061876

Nandwani, P., & Verma, R. (2021). A review on sentiment analysis and emotion detection from text. *Social Network Analysis and Mining*, *11*(1). https://doi.org/10.1007/s13278-021-00776-6

Neff, K. D. (2011). Self-compassion, self-esteem, and well-being. *Social and Personality Psychology Compass*, *5*(1), 1–12. https://doi.org/10.1111/j.1751-9004.2010.00330.x

Norman, K. P., Govindjee, A., Norman, S. R., Godoy, M., Cerrone, K. L., Kieschnick, D. W., & Kassler, W. (2020). Natural language processing tools for assessing progress and outcome of two veteran populations: Cohort study from a novel online intervention for posttraumatic growth. *JMIR Formative Research*, *4*(9), e17424. https://doi.org/10.2196/17424

Park, C. L. (2010). Making sense of the meaning literature: An integrative review of meaning making and its effects on adjustment to stressful life events. *Psychological Bulletin*, *136*(2), 257–301. https://doi.org/10.1037/a0018301

Park, A., Conway, M., & Chen, A. T. (2018). Examining thematic similarity, difference, and membership in three online mental health communities from reddit: A text mining and visualization approach. *Computers in Human Behavior*, *78*, 98–112. https://doi.org/10.1016/j.chb.2017.09.001

Pennebaker, J. W., Boyd, R. L., Booth, R. J., Ashokkumar, A., & Francis, M. E. (2022). *Linguistic Inquiry and Word Count: LIWC-22*. Pennebaker Conglomerates. https://www.liwc.app

Peterson, C., & Seligman, M. E. P. (2004). *Character strengths and virtues: A handbook and classification*. Oxford University Press.

Proellochs, N., & Feuerriegel, S. (2023). SentimentAnalysis: Dictionary-based sentiment analysis. R package version 1.3-5. https://CRAN.R-project.org/package=SentimentAnalysis

Proferes, N., Jones, N., Gilbert, S., Fiesler, C., & Zimmer, M. (2021). Studying reddit: A systematic overview of disciplines, approaches, methods, and ethics. *Social Media + Society*, *7*(2). https://doi.org/10.1177/20563051211019004

R Core Team. (2023). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Rand, K. L., & Cheavens, J. S. (2012). Hope theory. In S. J. Lopez & C. R. Snyder (Eds.), *Oxford Handbooks Online*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195187243.013.0030

Reddit.com. (2013). Trauma toolbox. https://www.reddit.com/r/traumatoolbox/

Rinker, W. T. (2018). qdapDictionaries: Dictionaries and word lists for the 'qdap' package. R package version 1.0.7. https://CRAN.R-project.org/package=qdapDictionaries

Rivera, I. (2023). RedditExtractoR: Reddit data extraction toolkit. R package version 3.0.9. https://CRAN.R-project.org/package=RedditExtractoR.

Sametoğlu, S., Pelt, D. H. M., Eichstaedt, J. C., Ungar, L. H., & Bartels, M. (2023). The value of social media language for the assessment of wellbeing: A systematic review and meta-analysis. *The Journal of Positive Psychology*, *19*(3), 471–489. https://doi.org/10.1080/17439760.2023.2218341

Scrignaro, M., Marini, E., Magrin, M. E., & Borreani, C. (2017). Emotive and cognitive processes in cancer patients: Linguistic profiles of post-traumatic growth. *European Journal of Cancer Care*, *27*(1), e12620. https://doi.org/10.1111/ecc.12620

Seligman, M. E. P. (2011). *Flourish: A visionary new understanding of happiness and well-being*. New York: Free Press.

Seligman, M. E. P. (2018). PERMA and the building blocks of well-being. *The Journal of Positive Psychology*, *13*(4), 333–335. https://doi.org/10.1080/17439760.2018.1437466

Sik, D., Németh, R., & Katona, E. (2021). Topic modelling online depression forums: Beyond narratives of self-objectification and self-blaming. *Journal of Mental Health*, *32*(2), 386–395. https://doi.org/10.1080/09638237.2021.1979493

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology, 29*(1), 24–54. https://doi.org/10.1177/0261927X09351676

Tedeschi, R. G., & Calhoun, L. G. (1995). *Trauma & transformation: Growing in the aftermath of suffering*. Sage Publications, Inc. https://doi.org/10.4135/9781483326931

Tedeschi, R. G., & Calhoun, L. G. (1996). The posttraumatic growth inventory: Measuring the positive legacy of trauma. *Journal of Traumatic Stress*, *9*(3), 455–471. https://doi.org/10.1002/jts.2490090305

Tedeschi, R. G., & Calhoun, L. G. (2004). Target article: "posttraumatic growth: Conceptual foundations and empirical evidence". *Psychological Inquiry*, *15*(1), 1–18. https://doi.org/10.1207/s15327965pli1501_01

van der Velden, P. G., Bosmans, M. W., & Scherpenzeel, A. C. (2013). The burden of research on trauma for respondents: A prospective and comparative study on respondents evaluations and predictors. *PLoS ONE*, *8*(10). https://doi.org/10.1371/journal.pone.0077266 van Zyl, L. E., & Rothmann, S. (2022). Grand challenges for positive psychology: Future perspectives and opportunities. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.833057

Vieselmeyer, J., Holguin, J., & Mezulis, A. (2017). The role of resilience and gratitude in posttraumatic stress and growth following a campus shooting. *Psychological Trauma: Theory, Research, Practice, and Policy*, *9*(1), 62–69. https://doi.org/10.1037/tra0000149

World Health Organisation. (2023, January). International Classification of Diseases (ICD). https://icd.who.int/en

Yu, C., Jannasch-Pennell, A., & DiGangi, S. (2014). Compatibility between text mining and qualitative research in the perspectives of grounded theory, content analysis, and reliability. *The Qualitative Report*. https://doi.org/10.46743/2160-3715/2011.1085

Zhang, Y., Chen, M., & Liu, L. (2015). A review on text mining. *2015 6th IEEE International Conference on Software Engineering and Service Science (ICSESS)*. https://doi.org/10.1109/icsess.2015.7339149

Zheng, L., Lu, Q., & Gan, Y. (2019). Effects of expressive writing and use of cognitive words on meaning making and post-traumatic growth. *Journal of Pacific Rim Psychology*, *13*. https://doi.org/10.1017/prp.2018.31

Appendix A

List of Investigated Positive Psychological Theories and Models and Respective PPCs

Ten Pleasant Emotions (Fredrickson, 2009)

Joy, gratitude, calm, interest, hope, pride, cheer, inspiration, awe, and *love*.

Values in Action Character Strengths (Peterson & Seligman, 2004)

Wisdom, courage, humanity, citizenship, temperance, transcendence, creativity, curiosity, judgement, perspective, bravery, perseverance, zest, honesty, social intelligence, kindness, love, leadership, fairness, teamwork, forgiveness, love of learning, gratitude, spirituality, self-regulation, humility, appreciation of beauty, prudence, hope, and *humour.*

PERMA Model (Seligman, 2011)

Positive emotions, engagement, positive relationships, meaning, and *accomplishment.*

Self-determination Theory (Deci & Ryan, 2008)

Self-determination, *determination, autonomy, competence, relatedness,* and *motivation.*

Compassion and Self-compassion (Gilbert, 2020; Neff, 2011)

Compassion and *self-compassion.*

Resilience (Bonanno et al., 2011)

Resilience.

Post-Traumatic Growth Inventory (Tedeschi & Calhoun, 1996)

Post-traumatic growth, new possibilities, relating to others, personal strength, spiritual change, appreciation of life.

Appendix B

The following Tables 8 to 14 provide an overview of results from *LIWC's Word Frequencies* analysis of identified related terms and PPCs in the subreddit, their negation frequency, and how many posts contain the term in absolute and relative frequency. Concepts which are stated multiple times between theories were marked with brackets the second time they appear.

Table 8

Word Frequencies, Negation Frequencies, and Descriptive Statistics of PPCs and Related Terms from Ten Pleasant Emotions (Fredrickson, 2009)

Word	Frequency	Negation Frequency	Posts with Word	% of Posts with Word
gratitude	7	0	7	0.16
grateful	35	1	33	0.76
gratefull	1	1	1	0.02
gratefully	1	0	1	0.02
thank	621	10	552	12.79
thanks	196	3	183	4.24
thankfully	11	0	11	0.25
thankyou	3	0	3	0.07
thankful	6	1	6	0.14
thankkkks	1	0	1	0.02
joy	45	1	37	0.86
enjoy	77	3	59	1.37
enjoyed	15	2	14	0.32
enjoyable	9	0	8	0.19

enjoying	11	1	11	0.25
joys	2	0	2	0.05
enjoyment	5	0	5	0.12
joyful	2	0	2	0.05
hope	422	11	371	8.59
hoping	49	0	48	1.11
hopeful	9	0	9	0.21
hopes	13	0	12	0.28
hoped	9	0	8	0.19
calm	96	2	80	1.85
calming	26	0	23	0.53
calmer	8	1	8	0.19
calmly	6	0	6	0.14
calmed	10	0	10	0.23
calms	3	0	3	0.07
calmness	1	0	1	0.02
interest	32	2	31	0.72
interesting	49	2	46	1.07
interested	70	10	60	1.39
interests	12	0	12	0.28
interestingly	1	0	1	0.02
pride	5	0	5	0.12
proudly	3	0	3	0.07

proudness	1	0	1	0.02
cheer	0	0	0	0
cheering	3	1	3	0.07
cheerful	1	0	1	0.02
cheered	1	0	1	0.02
inspiration	2	0	2	0.05
inspire	4	0	4	0.09
inspired	7	0	7	0.16
inspires	2	1	2	0.05
inspirational	1	0	1	0.02
awe	1	0	1	0.02
awesome	27	0	25	0.58
love	531	40	370	8.57
loved	125	3	105	2.43
loves	34	3	32	0.74
lovely	22	0	22	0.51
loving	61	7	53	1.23
loveable	3	1	3	0.07
lovable	5	0	5	0.12
lovingly	1	0	1	0.02
lovies	1	0	1	0.02
inlove	1	0	1	0.02
lover	1	0	1	0.02

lovebombing	1	0	1	0.02
beloved	2	0	2	0.05

Note. PPCs = positive psychological concepts.

Table 9

Word Frequencies, Negation Frequencies, and Descriptive Statistics of PPCs and Related Terms from Values In Action Character Strengths (Peterson & Seligman, 2004)

Word	Frequency	Negation Frequency	Posts with Word	% of Posts with Word
wisdom	9	0	9	0.21
wise	20	4	19	0.44
wisely	2	0	2	0.05
wiser	1	0	1	0.02
wisemind	1	0	1	0.02
courage	20	0	19	0.44
encouragement	7	0	7	0.16
encourage	26	2	25	0.58
encouraged	5	0	5	0.12
encourages	4	1	4	0.09
courageous	2	0	2	0.05
humanity	4	0	4	0.09
citizenship	1	0	1	0.02
citizen	1	1	1	0.02
citizens	1	0	1	0.02
temperance	0	0	0	0

transcendence	0	0	0	0
transcend	1	0	1	0.02
creativity	6	0	6	0.14
creative	15	0	14	0.32
creatively	1	0	1	0.02
curiosity	7	0	7	0.16
curiousity	2	0	2	0.05
curiously	1	0	1	0.02
curious	36	0	33	0.76
judgement	12	2	12	0.28
judgment	10	0	10	0.23
judgemental	4	0	4	0.09
judgmental	5	0	4	0.09
judgements	2	0	2	0.05
judgments	2	0	2	0.05
judge	27	9	23	0.53
judging	6	2	6	0.14
judged	6	0	6	0.14
judges	1	0	1	0.02
perspective	65	1	57	1.32
perspectives	18	0	16	0.37
bravery	1	0	1	0.02
brave	25	1	19	0.44

bravely	1	0	1	0.02
bravest	1	0	1	0.02
perseverance	0	0	0	0
persevere	1	0	1	0.02
persevered	1	0	1	0.02
zest	0	0	0	0
honesty	4	0	4	0.09
honestly	130	10	112	2.59
honest	69	1	63	1.46
social intelligence	0	0	0	0
social	119	8	94	2.18
socially	9	0	9	0.21
socializing	5	1	5	0.12
socialize	5	0	5	0.12
socialisation	1	0	1	0.02
kindness	30	1	26	0.60
kindly	3	0	3	0.07
kindest	3	0	3	0.07
kindhearted	1	0	1	0.02
kinder	4	0	4	0.09
(love)	531	40	370	8.57
(loved)	125	3	105	2.43
(loves)	34	3	32	0.74

(lovely)	22	0	22	0.51
(loving)	61	7	53	1.23
(loveable)	3	1	3	0.07
(lovable)	5	0	5	0.12
(lovingly)	1	0	1	0.02
(lovies)	1	0	1	0.02
(inlove)	1	0	1	0.02
(lover)	1	0	1	0.02
(lovebombing)	1	0	1	0.02
(beloved)	2	0	2	0.05
leadership	0	0	0	0
lead	48	2	46	1.07
leading	15	1	14	0.32
leads	12	1	12	0.28
leader	5	0	5	0.12
leaders	2	0	2	0.05
led	43	2	38	0.88
fairness	0	0	0	0
fair	48	14	44	1.02
fairly	25	1	24	0.56
teamwork	0	0	0	0
team	22	2	14	0.32
teams	4	0	4	0.09

teammates	2	0	2	0.05
teamed	1	0	1	0.02
teaming	1	0	1	0.02
forgiveness	64	9	33	0.76
forgive	95	18	67	1.55
forgiving	33	4	27	0.63
forgiven	8	2	8	0.19
forgives	3	0	1	0.02
forgave	6	0	6	0.14
forgibe	1	1	1	0.02
love of learning	0	0	0	0
love learn	1	0	1	
(love)	531	40	370	8.57
(loved)	125	3	105	2.43
(loves)	34	3	32	0.74
(lovely)	22	0	22	0.51
(loving)	61	7	53	1.23
(loveable)	3	1	3	0.07
(lovable)	5	0	5	0.12
(lovingly)	1	0	1	0.02
(lovies)	1	0	1	0.02
(inlove)	1	0	1	0.02
(lover)	1	0	1	0.02

(lovebombing)	1	0	1	0.02
(beloved)	2	0	2	0.05
learn	147	7	127	2.94
learned	107	8	96	2.22
learning	90	3	79	1.83
learnings	1	0	1	0.02
learnt	6	1	6	0.14
relearning	1	0	1	0.02
(gratitude)	7	0	7	0.16
(grateful)	35	1	33	0.76
(gratefull)	1	1	1	0.02
(gratefully)	1	0	1	0.02
(thank)	621	10	552	12.79
(thanks)	196	3	183	4.24
(thankfully)	11	0	11	0.25
(thankyou)	3	0	3	0.07
(thankful)	6	1	6	0.14
(thankkkks)	1	0	1	0.02
spirituality	3	0	2	0.05
spiritual	21	0	12	0.28
spirit	6	0	6	0.14
spiritually	2	0	2	0.05
spirited	2	0	2	0.05

religion	14	1	12	0.28
religious	35	3	33	0.76
self regulation	0	0	0	0
humility	2	0	2	0.05
appreciation of beauty	0	0	0	0
appreciate	125	3	120	2.78
appreciation	3	0	3	0.07
appreciative	1	0	1	0.02
appreciated	44	1	44	1.02
appreciating	1	0	1	0.02
appreciatedd	1	0	1	0.02
beauty	12	0	7	0.16
beautiful	67	1	60	1.39
beautifully	2	0	2	0.05
prudence	0	0	0	0
prudent	1	0	1	0.02
prude	1	0	1	0.02
(hope)	422	11	371	8.59
(hoping)	49	0	48	1.11
(hopeful)	9	0	9	0.21
(hopes)	13	0	12	0.28
(hoped)	9	0	8	0.19

humour	3	0	3	0.07
humor	11	0	8	0.19
humorous	1	0	1	0.02

Note. PPCs = positive psychological concepts.

Table 10

Word Frequencies, Negation Frequencies, and Descriptive Statistics of PPCs and Related Terms from PERMA Model (Seligman, 2011)

Word	Frequency	Negation Frequency	Posts with Word	% of Posts with Word
positive emotions	1	0	1	0.02
positive	83	4	64	1.48
positives	5	1	5	0.12
positively	5	0	5	0.12
engagement	3	0	2	0.05
engage	39	0	32	0.74
engaging	13	1	13	0.30
engaged	7	0	7	0.16
positive relationships	0	0	0	0
(positive)	83	4	64	1.48
(positives)	5	1	5	0.12
(positively)	5	0	5	0.12
positive relationship	1	0	1	0
relationship	414	22	258	5.98
relationships	141	5	111	2.57

friendships	18	2	18	0.42
friendship	33	1	25	0.58
friends	467	28	280	6.49
friend	458	14	288	6.67
friendly	10	0	10	0.23
friendliness	1	0	1	0.02
boyfriend	115	1	83	1.92
boyfriends	9	0	9	0.21
girlfriend	37	1	27	0.63
befriending	1	0	1	0.02
befriended	4	0	4	0.09
bestfriend	3	0	2	0.05
meaning	36	2	34	0.79
meaningful	13	1	13	0.30
accomplishment	3	1	3	0.07
accomplishments	5	2	5	0.12
accomplish	6	0	5	0.12
accomplishes	1	0	1	0.02
accomplishement	1	0	1	0.02
accomplished	9	0	8	0.19

Note. PPCs = positive psychological concepts.

Table 11

Word Frequencies, Negation Frequencies, and Descriptive Statistics of PPCs and Related Terms from Self-determination Theory (Deci & Ryan, 2008)

Word	Frequency	Negation Frequency	Posts with Word	% of Posts with Word
self determination	0	0	0	0
determination	1	0	1	0.02
determine	3	0	3	0.07
determined	9	0	7	0.16
autonomy	3	0	3	0.07
autonomously	2	0	2	0.05
autonomic	2	0	2	0.05
competence	0	0	0	0
competent	6	3	5	0.12
competently	1	0	1	0.02
relatedness	0	0	0	0
relate	72	1	68	1.58
relation	8	2	7	0.16
relations	4	0	4	0.9
(relationship)	414	22	258	5.98
(relationships)	141	5	111	2.57
relatives	8	0	7	0.16
relative	14	1	13	0.30

motivation	17	1	15	0.35
motivating	2	0	2	0.05

Note. PPCs = positive psychological concepts.

Table 12

Word Frequencies, Negation Frequencies, and Descriptive Statistics of PPCs and Related Terms from Compassion and Self-compassion (Gilbert, 2020; Neff, 2011)

Word	Frequency	Negation Frequency	Posts with Word	% of Posts with Word
compassion	45	0	42	0.97
compassionate	25	2	24	0.56
self compassion	2	0	2	0.05

Note. PPCs = positive psychological concepts.

Table 13

Word Frequencies, Negation Frequencies, and Descriptive Statistics of PPCs and Related Terms from Resilience (Bonanno et al., 2011)

Word	Frequency	Negation Frequency	Posts with Word	% of Posts with Word
resilience	5	0	5	0.12
resilient	9	0	8	0.19
resiliency	3	1	3	0.07

Note. PPCs = positive psychological concepts.

Table 14

Word Frequencies, Negation Frequencies, and Descriptive Statistics of PPCs and Related Terms from PTGI (Tedeschi & Calhoun, 1996)

Word	Frequency	Negation Frequency	Posts with Word	% of Posts with Word
post traumatic growth	1	0	1	0.02

growth	20	0	17	0.39
grow	76	5	73	1.69
growing	98	5	83	1.92
grown	26	1	24	0.56
grows	3	0	3	0.07
grew	79	2	73	1.69
new possibilities	0	0	0	0
possibility	29	1	27	0.63
possibly	42	3	37	0.86
possibilities	7	0	6	0.14
relating to others	0	0	0	0
(relate)	72	1	68	1.58
(relation)	8	2	7	0.16
(relations)	4	0	4	0.9
(relationship)	414	22	258	5.98
(relationships)	141	5	111	2.57
(relatives)	8	0	7	0.16
(relative)	14	1	13	0.30
personal strengths	0	0	0	0
strength	42	0	34	0.79
strengthening	4	0	4	0.09
strengthen	1	0	1	0.02
spiritual change	0	0	0	0

(spirituality)	3	0	2	0.05
(spiritual)	21	0	12	0.28
(spirit)	6	0	6	0.14
(spiritually)	2	0	2	0.05
(spirited)	2	0	2	0.05
(religion)	14	1	12	0.28
(religious)	35	3	33	0.76
appreciation of life	0	0	0	0
(appreciate)	125	3	120	2.78
(appreciation)	3	0	3	0.07
(appreciative)	1	0	1	0.02
(appreciated)	44	1	44	1.02
(appreciating)	1	0	1	0.02
(appreciated)	1	0	1	0.02

Note. PPCs = positive psychological concepts, PTGI = post-traumatic growth inventory.