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The semantic inflation of "trauma" in psychology

Trauma is an increasingly prominent concept in psychology and society at large. According to the theory of concept creep, it is one of several harm-related concepts that have undergone semantic inflation in recent decades, expanding to encompass new kinds of phenomena (horizontal expansion) and less severe phenomena (vertical expansion). Previous research has demonstrated that "trauma" has come to be used in a widening range of semantic contexts, implying horizontal expansion, but has not investigated vertical expansion. The present study developed a methodology for evaluating vertical expansion and implemented it using an English-language corpus of 825,628 scientific psychology article abstracts from 1970 to 2017. Findings indicate that "trauma" has come to be used in less severe contexts, and this trend may be linked to its rising frequency of use. These findings support the predictions of the concept creep theory and provide a new method for investigating the language dynamics of harm-related concepts.

Key words: trauma, harm, concept creep, semantic inflation, language dynamics

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Word meanings are malleable, changing over time in response to cultural shifts and the internal dynamics of language. Studies of historical semantics have documented a variety of change processes through which words broaden or narrow their reference, weaken, or strengthen their meanings, lose or gain semantic content, or become obsolete (Bloomfield 1993; Hopper & Traugott, 1993). For example, at one point in time, "awesome" meant to be capable of inspiring awe, but, more recently, its meaning has been bleached to a general expression of approval. In Old English, "mete" referred to all food, but today it refers only to animal flesh. Once the domain of historical linguists, these processes of semantic change are increasingly a focus of computational research (Dubossarsky et al., 2017; Hamilton et al., 2016).

Semantic change processes are also the focus of recent social psychological research on concept creep. Haslam (2016) proposed that concepts related to harm have progressively broadened their meanings over the last half-century and provided case studies of psychological concepts of abuse, addiction, bullying, prejudice, and trauma. Haslam argued that this semantic expansion takes two primary forms. Horizontal expansion, or creep, occurs when concepts expand to incorporate qualitatively new phenomena by incorporating new semantic domains, for example, "bullying" referring to digitally mediated aggression (i.e., "cyber-bullying"). Vertical expansion occurs when a concept's meaning extends to cover less severe phenomena. Examples include cases when the criteria for diagnosing a mental illness are relaxed or the threshold for applying a concept is lowered (e.g., depressive and anxiety disorders lowering their diagnostic threshold; Horwitz & Wakefield, 2007, 2012). Horizontal creep resembles metaphor because it involves extending the meaning of a word to a referent that is analogous to the original referent (e.g., extending the use of "addiction" to include compulsive video gaming because it resembles physiological dependency on an ingested substance). Vertical creep resembles hyperbole because a word comes to be used to refer to a less intense or severe referent in a way that could appear exaggerated (e.g., using "trauma" to refer to a disappointing exam result).

Concept creep has generated a growing theoretical and empirical literature. Theorists have speculated that concepts of harm may have expanded partially due to declining levels of exposure to harm in Western societies (cf. Pinker, 2011), an increasing cultural sensitivity to harm, and the rise of harm-based morality (Graham et al., 2013). Another proposed factor is the deliberate efforts of "opprobrium entrepreneurs" who seek to shift conceptual boundaries for political purposes (Sunstein, 2018). The potentially ambivalent effects of concept creep have been explored by Haslam et al. (2020). On the negative side, concept creep may fuel social and political conflict by amplifying disagreement about what counts as harm and by generating polarized perceptions of victims and perpetrators through the process of "moral typecasting" (Gray & Wegner, 2009). Broadened harm concepts may lead genuinely harmful events to be trivialized (Dakin et al., 2023) and may impose limits on free expression through expanded definitions of intolerable harm. Expanding harm concepts may also undermine personal resilience (Jones & McNally, 2022). On the positive side, concept creep may promote desirable social change by problematizing harmful behavior that had previously been tolerated and by extending care and respect to people previously denied it. For instance, broadening the concept of mental disorder to include new conditions (e.g., including PTSD in the DSM-III) allows people whose suffering was previously dismissed to have it recognized and treated.

Empirical research to date has primarily addressed the historical phenomenon of concept creep indirectly by examining the implications of holding broader harm concepts. Studies have shown that people who are politically liberal, empathetic, women, high on personal vulnerability, and who endorse harm-based morality tend to hold more inclusive concepts (McGrath et al., 2019). Some studies have examined historical patterns. For example, a study of the Google Books corpus revealed that the usage of words representing harm-based morality rose from 1980 to 2007 (Wheeler et al., 2019), consistent with the proposed timing of the rising sensitivity to harm hypothesized to underpin concept creep. Fabiano and Haslam (2020) found evidence against propositions that concepts of mental disorder have broadened in the American psychiatric diagnostic manual from 1980 to 2013. Nevertheless, relatively little research has explored concept creep as a historical change process.

The Concept Creep of Trauma

One harm-related concept that merits special historical attention is trauma. Haslam and McGrath (2020) argue that this concept has progressively expanded its meaning over the past century. In the late 19th century, "trauma" referred exclusively to physical wounds, until this meaning was metaphorically extended to include psychological injuries as well – a clear case of horizontal concept creep. More recently, following the introduction of the post-traumatic stress disorder (PTSD) diagnosis in the DSM-III (American Psychological Association, 1980), concerns have been raised that criteria for defining traumatic events have undergone significant vertical creep as well (Long & Elhai, 2009; McNally, 2016). Initially, a traumatic event had to evoke symptoms of distress in most people and fall outside of usual human experiences. Later editions of the DSM relaxed this requirement to include indirectly, or vicariously, experienced events and experiences that were developmentally inappropriate rather than seriously endangering life or limb. Whereas the initially listed examples of traumatic events were rape, assault, military combat, natural disasters, and car accidents, less catastrophic stressors such as business losses and marital conflict came to be added later. This trend towards identifying less extreme adversities as traumas has permeated the public consciousness – sometimes potentially trivializing the suffering of people whose experiences fit the earlier stringent definition of a catastrophic life event. For example, media outlets now include learning about disturbing stories second-hand (Lees, 2008), experiencing microaggressions (Vassell, 2020), and having certain presidents elected (Gross, 2016) as instances of trauma. Therefore, "trauma" has come to be employed in ways that may appear hyperbolic relative to its earlier meaning.

Semantic Change Detection

Demonstrating semantic changes such as these has recently become possible through advances in computational linguistics. An array of techniques (e.g., Tahmasebi et al., 2018) has been developed to detect and quantify patterns of diachronic semantic change. These techniques are mainly based on the distributional hypothesis (Firth, 1957), according to which words that occur in similar contexts tend to be semantically close to each other. Using a corpus of over 800,000 scientific abstracts published in psychology journals from 1970 to 2017, Vylomova et al. (2019) and Vylomova and Haslam (2020) have employed some of these linguistic techniques to test whether a sample of harm-related concepts have broadened their meanings as predicted by the theory of concept creep. Semantic breadth was estimated as the average cosine similarity of a concept's semantic vectors, and changes in their breadth were tracked over time. Vylomova et al. (2019) demonstrated that many harm-related concepts broadened in the corpus over the study period. For example, from the 1980s to the 2010s, the mean cosine similarity of contextual usages of "trauma" declined, indicating a rising diversity in the semantic contexts in which the word appeared, and it became associated less with "physical" and more with "psychological," "stress," and "sexual," demonstrating its expansion beyond physical injury into the psychological domain. These findings support the claim of concept creep for trauma.

What might be driving this semantic expansion is unclear, but one possibility is that it results from the increasing salience of the trauma concept. As the concept rises in popularity, it may come to be used in new contexts, thereby producing semantic expansion. Analyses of the Google Books corpus indicate that "trauma" and its cognates have risen in relative frequency in recent decades, and an analysis of the psychology abstracts corpus showed an even steeper trend (Vylomova et al., 2019). A newly implemented econometric dynamic modelling method demonstrated that the rising relative frequency of "trauma" had a unique predictive relationship with its semantic breadth, consistent with this possibility (Haslam et al., 2021).

Findings such as these provide substantial support for the concept creep hypothesis. Some harm-related concepts, including trauma, can be shown to have broadened their meanings in large text corpora using rigorous computational methods, and one possible driver of this semantic broadening – the rising relative frequency of a concept – has been identified (Haslam et al., 2021; Vylomova et al., 2019; Vylomova & Haslam, 2021). However, this research is limited. Vertical expansion is a key dimension of concept creep, and it is arguably the primary dimension for understanding the apparent dilution of the concept of trauma in recent years. Yet, existing methods of detecting semantic broadening cannot differentiate it from other types of semantic change. Cosine similarity-based methods model concept breadth as the diversity of contexts in which the concept appears. Therefore, they are mainly aligned with the horizontal dimension of concept creep (i.e., the qualitative range of phenomena to which the concept refers). Such methods cannot precisely evaluate whether the concept is being used to refer to quantitatively less severe or intense phenomena. Therefore, rigorous assessment of the vertical expansion of harm-related concepts such as trauma requires the development of a new methodology that can track shifts in the severity of the semantic contexts in which concepts appear.

The Present Study

In view of the absence of systematic evidence for the vertical expansion of harm-related concepts, and of a methodology for evaluating it, the present study aimed to develop such a methodology and to implement it in a corpus study of trauma using the psychology abstracts corpus employed in previous studies. We hypothesized that words associated with "trauma"—that is, words (and also specifically nouns) that appear in close proximity to it—would decline in mean severity over the study period. Severity was conceptualized as degree of intense negative emotional meaning or connotation of the associated words. A historical reduction in the degree to which "trauma" is associated with intense negative emotionality would be consistent with the claim that trauma has undergone vertical concept creep. We further hypothesized that this decline in severity would be prospectively predicted by the rising prevalence (relative frequency) of "trauma" in the corpus, consistent with the previously established role of rising frequency in the semantic broadening (horizontal creep) of trauma (Haslam et al., 2021). As "trauma" came to be used more frequently over time, we hypothesized that the severity of its associated words (and nouns in particular) would decrease.

Method

Materials

Psychology Corpus

To examine historical trends in the meaning of trauma in psychology, we used a corpus of psychology abstracts compiled in 2019. It comprised abstracts from 875 psychology journals, collected from the E-Research and PubMed databases, covering the period 1930–2019 (Vylomova et al., 2019). After removing duplicate records, copyright notices, book reviews, non-English abstracts, and editorials, the corpus contained 871,340 abstracts and 133,082,240 total words. Due to the relatively small number of abstracts in the first half of the 20th century, and only partial data from 2018–2019, we restricted our study to the 1970–2017 period. The corpus was preprocessed into analyzable format by tokenization (lowercasing, removal of punctuation and function words). Then, as is standard practice in corpus linguistics, the tokens were partitioned into distinct linguistic units and lemmatized into their base form (e.g., "ran," "runs," and "running" converted to the verb lemma run). Overall, the corpus provided a means to track shifts in the use of the term "trauma" within 825,628 abstracts representing a majority of English-language psychology articles published in this period.

Trauma Collocates Data

To capture the meaning of trauma in the corpus, we relied on methods of distributional semantics (Harris, 1954). The meaning of trauma was operationalized as the distribution of (lemmatized) words immediately collocating with (i.e., neighboring) the term "trauma" within a ± five-word context window (Gablasova et al., 2017). The lemma trauma appears 25,382 times in the corpus, resulting in 112,003 collocates representing 8,945 unique English lemmas, many repeated multiple times.

Warriner Norms Data

To evaluate the severity of the trauma collocates, we used normed valence and arousal ratings for English lemmas developed by Warriner et al. (2013). The dataset comprised norms for 13,915 English lemmas and was procured by psycholinguists for large scale studies. The present study used ratings on valence (i.e., the pleasantness of a stimulus) and arousal (i.e., the intensity of emotion provoked by a stimulus) made by 1,827 participants (16-87 years; 60% female). The valence scale ranged from 1 (*unhappy*) to 9 (*happy*). Its extremes represented feeling "completely unhappy, annoyed, unsatisfied, melancholic, despaired, bored" (low) and "happy, pleased, satisfied, contented, hopeful" (high). The arousal scale ranged from 1 (*calm*) to 9 (*excited*). Its extremes represented feeling "relaxed, calm, sluggish, dull, sleepy, unaroused" (low), and "stimulated, excited, frenzied, jittery, wide-awake, aroused" (high). We made the a priori decision to assess the severity of trauma-related words as the additive combination of negative valence (i.e., ratings representing a high level of unhappiness) and high arousal (i.e., ratings representing a high degree of arousal).

Measures

Development of the Severity Index

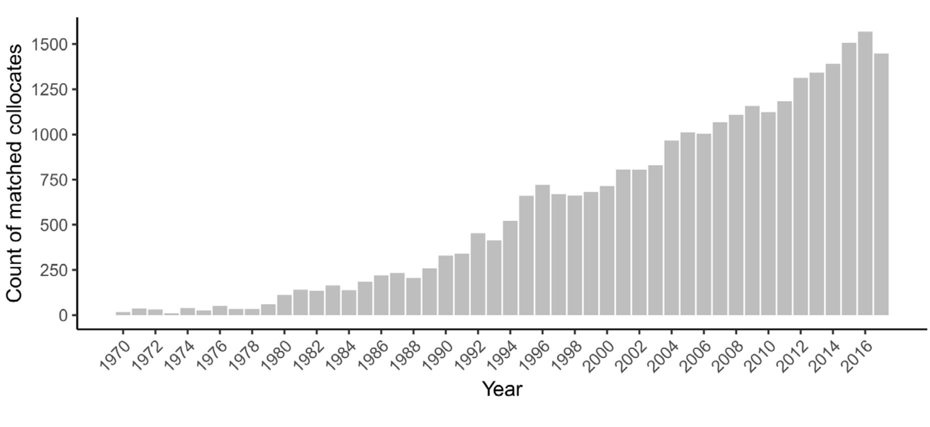
Trauma collocates that matched with lemmas in the Warriner et al. (2013) norms were identified and linked with the valence and arousal statistics from those norms, yielding 3,921 unique sentence-level, norm-matched trauma collocates. To form an index of severity, valence and arousal ratings for each lemma were combined, as more severe traumatic events or experiences would be expected to be both more unpleasant (i.e., negatively valenced) and more emotionally intense (i.e., high in arousal). To derive the severity score for each word, its valence rating from the Warriner et al. (2013) norms' 1-to-9 scale was reverse scored so that high scores represented negative valence. These scores were added to the word's arousal ratings to yield a severity index. For example, "war" and "murder" initially had valence norm ratings of 2.23 and 1.48, and arousal norm ratings of 6.27 and 6.24, respectively. Their reversed valence scores (where a 1 would become a 9 and vice versa) were 6.77 and 7.52. Their severity scores were therefore calculated as follows: 6.77 + 6.27 = 13.04 for "war" and 7.52 + 6.24 = 13.76 for "murder."By comparison, "peace" and "calm" had valence ratings of 7.75 and 6.89 (i.e., reversed ratings of 1.25 and 2.11), arousal ratings of 4.65 and 1.67, and resulting severity scores of 5.90 and 3.78, respectively. Therefore, the severity index captures continuous degrees of severity for individual words represented in the Warriner et al. (2013) norms that could range from 2 (low severity) to 18 (high severity).

Across the lemmas in the Warriner et al. (2013) norms, (negative) valence and arousal were positively correlated, $r(13{,}911) = .18$, $p < .001$. After restricting the Warriner et al. (2013) norms dataset to contain only lemmas that matched trauma collocates, valence and arousal correlated more strongly, $r(3{,}916) = .31$, $p < .001$. Very few trauma collocates that matched lemmas in the Warriner et al. (2013) norms appeared in the early years of the corpus (see Figure 1). To ensure sufficient data points, years before the collocate count reached double figures were excluded from the analysis, yielding a word list of 3,918 unique lemmas, without sentence-level context, from 1974 to 2017. This word list was employed in the hypothesis tests.

Development of the Noun List

Nouns were extracted from the complete set of trauma collocates to create a more restricted list. This subset was used to determine whether any change in

Figure 1. *Summed Count of Warriner Matched Trauma Collocates in the Psychology Corpus by Year*



the severity of the meaning of trauma was observable among words most likely to qualify as traumas (i.e., occurrences that might be traumatic events) given that events would normally be referred to by nouns. We systematically extracted this subset in a two-step procedure. In the first step, the 3,918 unique lemmas, without sentence-level context, were tagged individually for parts of speech. To reduce the likelihood of type I errors, a full distribution of tags was obtained for each lemma at the sentence level using the en_core_web_lg model within SpaCy (Honnibal & Montani, 2017). Table 1 shows the resulting distribution of tags for lemmas tagged as their part of speech at least once. In the second step, we selected a restricted set of collocates from the set of 3,396 lemmas appearing as nouns at least once at the sentence level by selecting those that appeared as nouns more than any other part of speech. This yielded a final subset of 2,117 lemmas that appeared predominantly as nouns in the context of "trauma."

Index construction

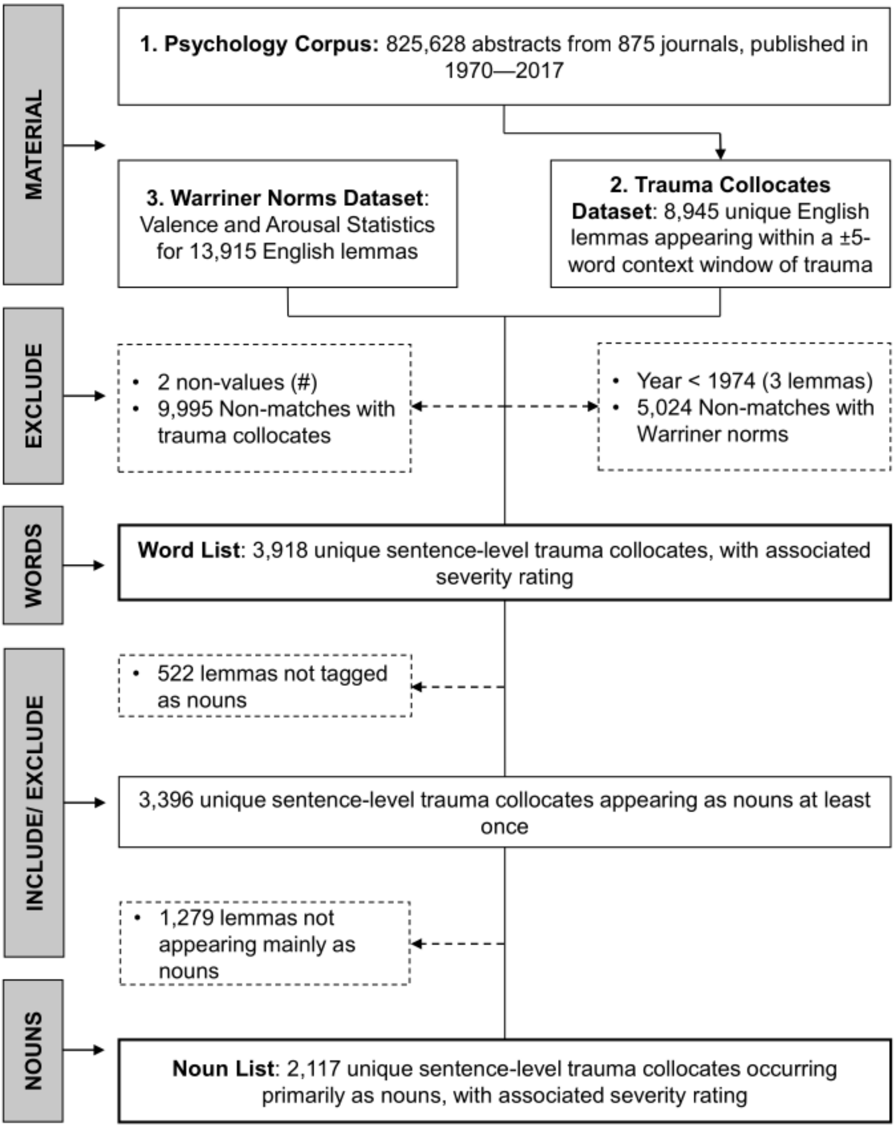
To assess the relative frequency of appearance of the concept of trauma for each year (1974—2017), we followed Vylomova and Haslam's (2021) previously established measure of the concept. First, words that shared the "trauma" word stem and occurred at least 50 times in the psychology corpus were selected: "trauma," "traumatic," and "traumatiz(+s)e." The summed relative frequency of these lemmas, as a proportion of all lemmas in the same year, served as the index of trauma concept frequency.

Two indices of the mean weighted severity of lemmas that co-occurred with "trauma" were computed. An "all words" index was derived by computing the average severity (based on summed valence and arousal ratings) of all 3,918 trauma collocates (weighted by each one's number of repetitions) for each year from 1974 to 2017. A "nouns only" index was derived in the same way but restricted to the 2,117 lemmas that appeared predominantly as nouns in the corpus. Figure 2 summarizes the dataset linkage and construction procedure. The final dataset, containing all raw time series indices, is available at: https://osf.io/b8v7d

Table 1. *Distribution of Parts of Speech for the Set of Trauma Collocates*

Parts of speech	Frequency
Nouns	*3396*
Adjectives	*2669*
Verbs	*2169*
Adverbs	*449*
Proper Nouns	*294*
Adpositions	*37*
Determiners	*26*
Interjections	*24*
Pronouns	*6*
Conjunctions	*3*

Figure 2. *Flowchart of the Procedure for Linking Datasets, Preprocessing, and Computing Word Lists*



Note. Bolded boxes emphasize the word lists used in the hypothesis tests.

Analytic Strategy

To test our first prediction that the severity of the meaning of trauma-related phenomena declined in the study period, we used the *R* Statistical Software (v4.1.2; R Core Team, 2021) to conduct regression analyses to determine whether the severity index decreased over time for all trauma-related words and for nouns only. Next, we conducted follow-up regressions to examine whether such decreases in the severity index occurred for its two components (valence and arousal). We note that the noun set was not statistically independent of the word set because it was based on a subset of the list of trauma collocates.

To test the second prediction that the reduced severity of trauma-related words and nouns was temporally related to the rising relative frequency of the trauma concept, we used the Stata Statistical Software (Release 17; StataCorp, 2021) to employ an autoregressive distributed lag model (ARDL) framework exemplified by Haslam et al. (2021). The ARDL model is typically found in econometrics to test hypotheses of predictive causality (Granger, 1980), whereby beliefs about causal effects are updated incrementally, and is similar to a cross-lagged approach, wherein the current value of a variable is predicted by its past values (i.e., its autoregressive component) and the past of multiple other variables (i.e., its lagged component). However, unlike cross-lagged models, the ARDL is specified by searching through all possible combinations of different numbers of lags for predictor variables to obtain the best-fitting model, thus solving the problem of endogeneity. Another advantage is its inclusion of higher-order lags as, even if nonstationarity is present, information about trends and other factors will be contained in past levels of the outcome variable by including higher-order lags for enacting controls (see Lüdtke & Robitzsch, 2022). Information about features of the data that may drive systematic nonstationarity are contained in the lags of the outcome variable, which are included in the model automatically as model specification is a function of model fit (including reasonable penalization for parsimony). Therefore, and in addition to inferences being limited to the short-run dynamics in the corpus timeframe, the ARDL framework is robust to the presence of nonstationarity in the data. Another advantage is the expectation that residuals are not serially correlated. While balancing the need for parsimony, the fitting procedure extracts relevant forms of autocorrelation by selecting optimal lags of the outcome variable when fitting it. Finally, the ARDL procedure is able to produce unbiased results in the case of a small sample size.

The ARDL models in the present context were specified as follows: annual scores on the severity index were predicted by (a) the score on the index in the previous year (and potentially at longer lags), (b) the relative frequency of "trauma" in the previous year (also potentially at longer lags), and (c) year (the trending variable). A potential causal role of the rising relative frequency of "trauma" in its declining severity would be established if the former had a significant (lagged) negative effect on the latter independent of the autoregressive and year effects.

First, variables were standardized given the different scaling of the variables in the model. Second, to search for the optimal ARDL lag order specification while reducing the chance of overfitting the data, a searching algorithm evaluated lag order between 10,000,000 possible lag combinations for the outcome and predictor variables using the AIC index (Akaike, 1974) to rank candidates to best explain the data as a system of lags (whereby the goal is to minimize the AIC) while accounting for constraints. In addition to variable specification, constraints included setting the maximum order of lag length to 6 years for the outcome variable and up to 7 years for the predictor. Third, the final models were specified according to the lag lengths selected in the optimization procedure. The total effect of the predictors was estimated by summing the standardized short-run coefficients from the best-fitting model for each predictor/outcome pair.

Results

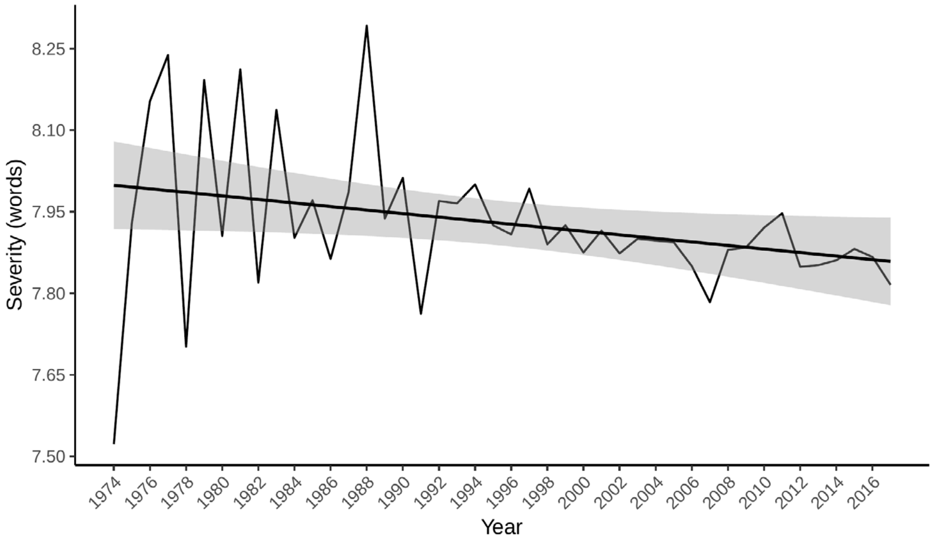
We constructed two linear models to test the hypothesized negative relationship between year and the severity index for words and for nouns from 1974 to 2017. There were no obvious violations of the assumptions of linearity, independence, normality, and homoscedasticity. The analyses revealed that year was negatively associated with the severity of trauma-related words, $\beta = -.30$, 95% CI [−.60, −.003], $p = .048$, Adj. $R^2 = 0.07$ (see Figure 3), and nouns, $\beta = -.37$, 95% CI [−.66, −.08], $p = .013$, Adj. $R^2 = 0.12$ (see Figure 4). These findings support the prediction that the severity of words associated with trauma, and by implication, the severity associated with the distributional meaning of trauma itself, declined over the study period.

Follow-up analyses examined the two components of the severity index (valence and arousal) to determine whether one or both components showed the negative year effects. Year was negatively associated with valence for all trauma-related words, $\beta = -0.32$, 95% CI [−0.61, −0.02], $p = .036$, Adj. $R^2 = 0.08$, but not for nouns, $\beta = -0.26$, 95% CI [−.56, .04], $p = .083$, Adj. $R^2 = 0.05$. Arousal declined statistically significantly for trauma-related nouns, $\beta = -0.44$, 95% CI [−.72, −.16], $p = .003$, Adj. $R^2 = 0.17$, but not for all words, $\beta = -0.17$, 95% CI [−0.16, 0.05], $p = .263$, Adj. $R^2 = 0.01$.

"Trauma" has increased in relative frequency in the psychology corpus over the last few decades (see Figure 5). As Figure 6 shows, in years when the relative frequency of "trauma" was high, its severity tended to be low (for all words: $r[42] = -0.32$, $p = .032$; for nouns: $r[42] = -0.40$, $p = .008$).

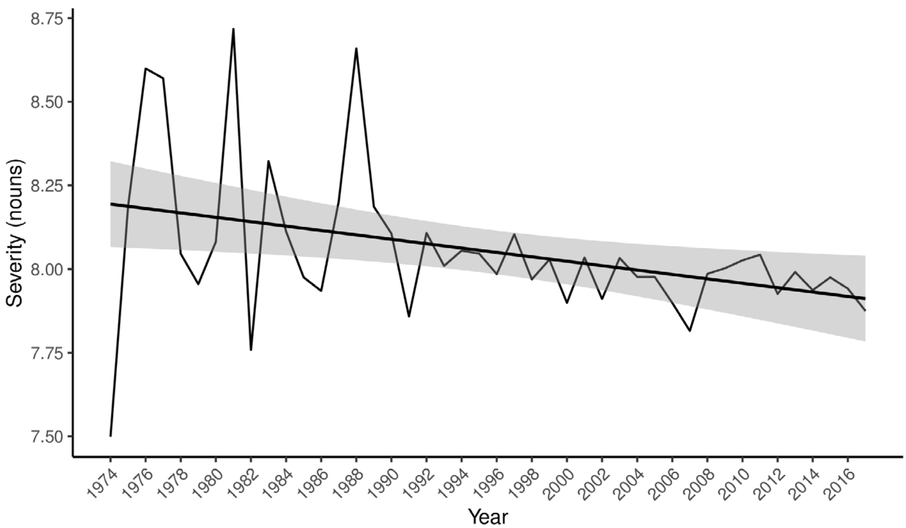
We ran the ARDL models to investigate the hypothesized effect of the rising relative frequency of "trauma" on the reduced semantic severity of all trauma-related words and nouns only in the psychology corpus from 1976—2017. Lag length specification for the model fitting the semantic severity of trauma-related words was six lags for trauma severity (words) and two lags for trauma relative frequency. For the model fitting the semantic severity of trauma-related nouns, the specification was: six lags for trauma severity (nouns) and four lags for frequency.

Figure 3. *Severity of Trauma (All Words) as a Function of Year Over the Study Period*



Note. The grey bars around the linear regression line graph the standard error of the estimate.

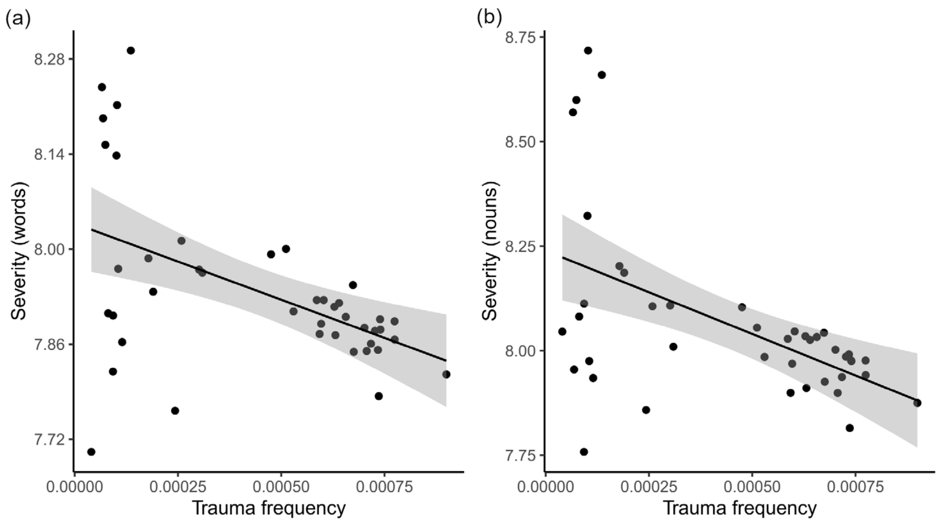
Figure 4. *Severity of Trauma (Nouns Only) as a Function of Year Over the Study Period*



Note. The grey bars around the linear regression line graph the standard error of the estimate.

Figure 5. *Relative Frequency of the Trauma Concept in the Psychology Corpus Over the Study Period*

Figure 6. *Relative Frequency of Trauma Against Severity Indices*



Note. Panel a: Severity indices for all words. Panel b: Severity indices for nouns only. Each dot represents a year in the time series data from 1976-2017. The grey bars represent the standard error around the line of best fit.

This restricted the time series to 1983—2017 ($T = 35$). Inspection of the predicted and residual values for the fitted models indicated no obvious violations of the assumptions of homoscedasticity and normality. As expected, partial autocorrelation plots indicated no obvious violations of the assumption of independence of residuals (see Figures S1 and S2 in the Appendix), confirmed by Bonferroni-corrected *t*-tests reporting that residual autocorrelations were not significantly different from zero. These results indicate that the error terms in both ARDL models were not serially correlated, implying that the models were correctly specified using the AIC criterion to select optimal lag order for the outcome and predictor variable.

The overall ARDL(6,2) model testing for a lagged relative frequency effect on the severity of trauma-related words was statistically significant, $F(9, 25) = 5.49$, $p < .001$, Adj. $R^2 = 0.54$. The model contained a statistically significant negative effect for year, $\beta = -0.06$, $t(34) = -2.27$, $p = .032$, a statistically significant negative overall autoregressive effect, coefficient = −2.42, $t(34) = -3.53$, $p = .002$, and the predicted statistically significant overall short-run effect of relative frequency, coefficient = −0.83, $t(34) = -2.49$, $p = .020$. Table 2 reports SEs and CIs. Individual short-run coefficients for lag weights are provided in the Appendix (see Table S1). The total effect of "trauma" relative frequency indicates that the rising prominence of "trauma" in the corpus is temporally related to the diminishing severity of trauma-related words, independent of time and endogenous (autoregressive) effects on severity.

The ARDL(6,4) model testing for a frequency effect on trauma-related nouns was also statistically significant, $F(11, 23) = 4.10$, $p = .002$, Adj. $R^2 = .50$. It contained a statistically nonsignificant predictive effect of year, $\beta = 0.03$, $t(34) = 1.02$, $p = .317$, a statistically significant negative overall short-run autoregressive effect, coefficient = −2.77, $t(34) = -4.39$, $p < .001$, and the predicted statistically significant overall short-run effect of relative frequency, coefficient = -1.95, $t(34) = -4.26$, $p < .001$. Table 3 reports SEs and CIs. All short-run coefficients for lag weights are provided in the Appendix (see Table S2). The total predictive effect of "trauma" relative frequency indicates that the relative frequency of references to "trauma" is temporally associated with the declining severity of nouns co-occurring with trauma, independent of time and autoregressive trends.

Table 2. *Predictive Effects for Autoregressive Distributed Lag When Relative Frequency of Trauma Predicts the Severity of Trauma-related Words in the Corpus*

Predictor	Coefficient	SE	*t*	*p*	CI^{95}
Trauma Relative Frequency (lagged)†	−0.83	0.33	−2.49	.020	[−1.51, −0.14]
Trauma Severity, Words (lagged)†	−2.42	0.68	−3.53	.002	[−3.83, −1.01]
Year	−0.06	0.03	−2.27	.032	[−0.12, −0.01]

Note. The best fitted model produced lag weights for Frequency (2 lags) and Severity (6 lags). † = standardized short-run coefficients of lags were summed to obtain the weighted sum (total predictive effect).

Table 3. *Predictive Effects for Autoregressive Distributed Lag Model When Relative Frequency of Trauma Predicts the Severity of Trauma-related Nouns*

Predictor	Coefficient	SE	t	p	CI[95]
Trauma Relative Frequency (lagged)†	−1.95	0.46	−4.26	< .001	[−2.90, −1.01]
Trauma Severity, Nouns (lagged)†	−2.77	0.63	−4.39	< .001	[−4.07, −1.47]
Year	0.03	0.03	1.02	.317	[−0.03, 0.09]

Note. The best fitted model produced lag weights for Frequency (4 lags) and Severity (6 lags). † = standardized short-run coefficients of lags were summed to obtain the weighted sum (total predictive effect).

Discussion

The present study developed a new methodology for assessing the vertical form of concept creep and tested it using the concept of trauma and a corpus of psychology article abstracts. In support of our first hypothesis, the severity of words collocating with "trauma," and also the subset of nouns, showed a significant reduction from 1974 to 2017. In support of our second hypothesis, the rising relative frequency of "trauma" in the corpus was associated with subsequent declines in the severity of trauma-related words and nouns, independent of year and autoregressive effects.

The first hypothesis findings are consistent with the general claim of concept creep theory—that "trauma" is increasingly used in less severe semantic contexts and that this trend can be observed in academic discourse. The findings complement previous findings employing pre-existing measures of semantic breadth, which have shown that trauma's meaning has become broader over time, including in psychology (Vylomova et al., 2019; Vylomova & Haslam, 2021). Those measures may be capable of demonstrating horizontal expansion, not vertical expansion, as they are not designed to differentiate the two forms of concept creep. As these are two forms of concept creep that may not co-occur (e.g., Fabiano & Haslam, 2020), the findings from the present study make a novel contribution to the concept creep literature. Although the distinct or overlapping causes of the two forms of trauma's semantic expansion are uncertain, the introduction of the PTSD diagnosis in 1980, which generated and continues to generate a large volume of psychological research, may be implicated. Overall, our research indicates that trauma has expanded its meaning in the past half-century, leading to its increased use in new semantic domains (horizontal creep) and to refer to less severe phenomena (vertical creep).

The implications of the present findings for academic psychology may be far-reaching. The vertical creep of trauma in psychology abstracts signals an increasingly relaxed threshold for what constitutes trauma. While recognition of traumatic experiences may have prompted respect and treatment for people in suffering (e.g., traumatized soldiers post-Vietnam war), broadening concepts of trauma may have negative consequences, including the overdiagnosis of PTSD. The latter concern of trauma experts (McNally, 2016; Tully et al., 2021) seems warranted when considering that classifying an event as traumatic by DSM-IV standards led to a 22% increase in exposure estimates relative to DSM-III (Breslau & Kessler, 2001). In addition, there is emerging evidence that broad concepts of trauma can have adverse effects for people who hold them, potentially making them more susceptible to post-traumatic reactions (Jones & McNally, 2021). Some social critics have charged that broadened concepts such as these contribute to "therapy culture" (Furedi, 2004) or cultures of fear (Furedi, 2018) and victimhood (Campbell & Manning, 2018), in which people become less resilient, more vulnerable, and more defined by their suffering. By loosening and broadening concepts of trauma, psychology may be contributing to the exaggeration of everyday adversities, which may have problematic social implications.

Consistent with recent research, we found that the declining mean severity of trauma is related to preceding rises in the prominence of trauma. Previous findings similarly revealed a frequency effect on indices of semantic breadth (Haslam et al., 2021), suggesting that both horizontal and vertical creep are distinct yet affected by concept frequency. To explain these findings, a suggestion made by Haslam (2016) merits attention: successful concepts can colonize new semantic territory by attracting the attention of researchers and practitioners. That is, concepts receiving more attention may have a greater likelihood of being applied across several contexts in the academic literature. For instance, attention paid to trauma in the trauma studies literature, which documents debate about its expansion (Weathers & Keane, 2007), may have propelled its vertical creep as researchers reference it more widely. In this way, the preoccupations of psychologists may influence the rise in reference to "trauma," leading to concept creep.

Implications for Concept Creep Theory

In developing a method to evaluate the declining semantic severity of harm-related concepts, this investigation pioneered a method to assess vertical concept creep, with trauma as its first application. Our method employs a count-based linguistic model linked to affective ratings to compute a severity index, in contrast to the cosine-similarity method used to compute semantic breadth in a manner more suitable to assess horizontal creep. The current findings demonstrate that concept creep has two distinct components. Therefore, future research must account for possible variations in both horizontal and vertical creep when investigating other harm-related concepts.

The relative frequency of references to a concept appears to be a crucial factor in understanding vertical concept creep. This is the first evidence, suggested by the lagged temporal relationship (Granger causality or predictive causation) demonstrated in the test of our second hypothesis, for a possible causal role of "trauma" relative frequency in expanding the meaning of trauma. The concept creep framework holds the factors responsible for it to be predominantly sociocultural (Haslam et al., 2020), yet findings from the present study imply a role for linguistic factors. Future research must disentangle the degree to which language dynamics (e.g., rising prominence, topical fluctuations) or sociocultural factors, such as shifts in values or sensitivity to harm, contribute to concept creep. The two sets of factors may not be independent, because broader cultural changes may be reflected in the rising prominence of particular concepts in everyday language and in academic discourse. Our newly developed method allows researchers to explore these influences and map their trajectories to large text corpora, an emerging practice in psychological research (Jackson et al., 2021).

The study also has some limitations that pose questions for future research. Although the list for trauma-related nouns was a strength of our study design, further work might involve more fine-grained analyses that focus attention on narrower sets of words. Future research could use Brysbaert et al.'s (2014) dataset to categorize abstract and concrete (experience-based) nouns, leaving human raters to judge whether they constitute event words. Furthermore, while using the psychology corpus was a strength, as concept creep attributes a substantial role to psychological concepts and discourses (Haslam, 2016), it may have limited the generalizability of our findings. To test scalability, our method should be applied in a general domain corpus (e.g., Haslam et al., 2021; Vylomova & Haslam, 2021). Ideally, future work will explore vertical and horizontal creep in other hypothetically harm-related concepts (e.g., mental disorder, abuse, harassment) in corpora representing other scholarly disciplines (e.g., psychiatry, law, politics).

Conclusion

The present study was the first to develop a method to systematically evaluate vertical semantic expansion in the context of "trauma." It laid the groundwork for further empirical research on concept creep by creating a way to index the semantic severity of harm-related concepts and establishing a potential causal factor implicated in concept creep: concept frequency or prominence. The utility of our method can be tested in the wider culture on other hypothetically harm-related concepts. Our dynamic modelling approach can be used to reveal additional causal factors that bear on concept creep. Clarifying the language dynamics of concept creep and evaluating its costs and benefits are crucial goals for academics who care about psychology's social contexts and ramifications.

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The data and scripts used in this study are available in the associated Open Science Framework repository: https://osf.io/xg758/ The source code for the semantic severity method is available at: https://github.com/naomibaes/SemanticSeverity

Conflict of Interest Disclosure

The Authors have no conflicts of interest to disclose.

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Research Ethics Statement

Institutional ethical approval was neither sought nor necessary as this corpus study comprised no human participants. Because this study did not require ethics approval, no ethical guidelines were explicitly followed.

Authorship Details

Naomi Baes: research concept and design, collection and/or assembly of data, data analysis and interpretation, writing the article, critical revision of the article, final approval of the article.

Ekaterina Vylomova: research concept and design, collection and/or assembly of data, critical revision of the article, final approval of the article.

Michael Zyphur: data analysis and interpretation, critical revision of the article, final approval of the article.

Nick Haslam: research concept and design, data analysis and interpretation, writing the article, critical revision of the article, final approval of the article.

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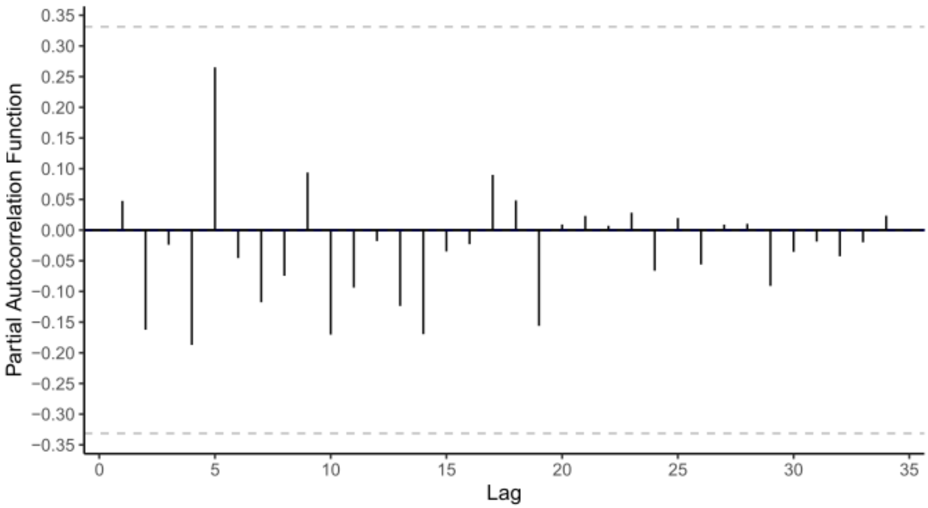
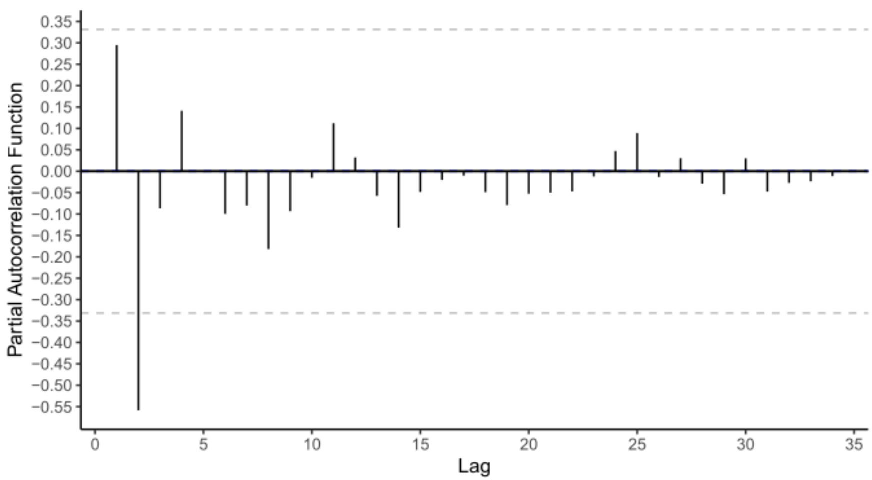
Appendix

Figure S1. *Correlogram of Residual Partial Autocorrelations for Autoregressive Distributed Lag Model Fitting the Severity of Trauma-related Words Predicted by the Relative Frequency of Trauma*



Note. The dashed line marks the 95% confidence interval.

Figure S2. *Correlogram of Residual Partial Autocorrelations for Autoregressive Distributed Lag Model Fitting the Severity of Trauma-related Nouns Predicted by the Relative Frequency of Trauma*



Note. The dashed line marks the 95% confidence interval.

Table S1. *Short-run Estimates for Autoregressive Distributed Lag Model When Relative Frequency of Trauma Predicts the Severity of Trauma-related Words in the Corpus*

Variable	Coefficient	SE	t	p	CI^{95}
Trauma Relative Frequency					
Lag 1	−0.11	0.52	−0.22	0.828	[−1.18, 0.95]
Lag 2	−0.71	0.53	−1.34	0.192	[−1.81, 0.38]
Trauma Severity, Words					
Lag 1	−0.34	0.17	−1.95	0.063	[−0.69, 0.19]
Lag 2	−0.27	0.18	−1.49	0.149	[−0.65, 0.10]
Lag 3	−0.85	0.17	−4.85	0.000	[−1.21, −0.49]
Lag 4	−0.28	0.18	−1.56	0.131	[−0.64, 0.09]
Lag 5	−0.25	0.17	−1.46	0.158	[−0.61, 0.10]
Lag 6	−0.43	0.15	−2.90	0.008	[−0.74, −0.13]
Year	−0.06	0.03	−2.27	0.032	[−0.12, −0.01]
Constant	121.38	53.52	2.27	0.032	[11.16, 231.60]

Note. The best fitted model produced lag weights for Frequency (2 lags) and Severity (6 lags).

Table S2. *Short-run Estimates for Autoregressive Distributed Lag Model When Relative Frequency of Trauma Predicts the Severity of Trauma-related Nouns in the Corpus*

Variable	Coefficient	SE	t	p	CI^{95}
Trauma Relative Frequency					
Lag 1	−0.75	0.49	−1.55	0.135	[−1.76, 0.25]
Lag 2	−0.48	0.61	−0.79	0.438	[−1.75, 0.78]
Lag 3	−0.01	0.62	0.02	0.988	[−1.27, 1.29]
Lag 4	−0.73	0.49	−1.49	0.149	[−1.73, 0.28]
Trauma Severity, Nouns					
Lag 1	−0.39	0.16	−2.36	0.027	[−0.73, −0.05]
Lag 2	−0.40	0.14	−2.90	0.008	[−0.69, −0.12]
Lag 3	−0.65	0.14	−4.64	0.000	[−0.94, −0.36]
Lag 4	−0.52	0.14	−3.60	0.001	[−0.82, −0.22]
Lag 5	−0.43	0.14	−3.15	0.004	[−0.71, −0.15]
Lag 6	−0.38	0.12	−3.03	0.006	[−0.63, −0.12]
Year	0.03	0.03	1.02	0.317	[−0.03, 0.09]
Constant	−57.10	55.67	−1.03	0.316	[−172.26, 58.06]

Note. The best fitted model produced lag weights for Frequency (4 lags) and Severity (6 lags).