Psychological Trauma and Emotional Upheaval as Revealed in Academic Writing:
The Case of COVID-19

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Abstract

The current paper used a preregistered set of language dimensions to indicate how scientists psychologically managed the COVID-19 pandemic and its effects. Study 1 evaluated over 1.8 million preprints from arXiv.org and assessed how papers written during the COVID-19 pandemic reflected patterns of psychological trauma and emotional upheaval compared to those written before the pandemic. The data suggest papers written during the pandemic contained more affect and more cognitive processing terms to indicate writers working through a crisis than papers written before the pandemic. Study 2 ($N = 74,744$ published PLoS One papers) observed consistent emotion results, though cognitive processing and analytic thinking patterns were inconsistent. Papers written specifically about COVID-19 contained more emotion than those not written about COVID-19. Finally, Study 3 ($N = 361,189$ published papers) replicated the Study 2 emotion results across more diverse journals and observed papers written during the pandemic contained a greater rate of cognitive processing terms, but a lower rate of analytic thinking, than papers written before the pandemic. These data suggest emotional upheavals are associated with psychological correlates reflected in the language of scientists at scale. Implications for psychology of language research and trauma are discussed.

Keywords: trauma, emotional upheaval, psychological distress, automated text analysis, COVID-19, pandemic

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People often respond to trauma or crises in psychologically predictable ways. Whether people are experiencing psychiatric disorders (Kleim et al., 2018) or romantic breakups (Seraj et al., 2021), they try to make meaning from a crisis after it occurs. Crucially, the psychological meaning-making process often appears in the language patterns of trauma victims. During the terrorist attacks of September 11th, for example, bloggers experienced shifts in their writing style after the attacks compared to before the attacks (Cohn et al., 2004). Bloggers wrote with more negative affect after the attacks and this level gradually returned to baseline nearly one week later, suggesting how people responded psychologically to the crisis during a critical time in their life. Other examinations of real-world trauma have found similar effects (Gortner & Pennebaker, 2003; Pennebaker & Harber, 1993; Stone & Pennebaker, 2002), suggesting those who experience or reflect on emotional upheavals often discuss their experiences, and language helps to reveal how people cope with distress dynamically over time (Pennebaker, 1997, 2011).

Perhaps the most salient, mass-scale crisis in recent history is the COVID-19 pandemic. Much has been written about the pandemic's mental health effects (Phelps & Sperry, 2020; Usher et al., 2020), its impact on socialization and social relationships (Bailenson, 2021; Krendl & Perry, 2021; Simard & Volicer, 2020), and the challenges it has presented to institutions (e.g., education) (Toquero, 2020; Williamson et al., 2020). An underreported or perhaps overlooked part of the pandemic is its impact on the academic research community. Some suggest academia has inadequately and inequitably responded to the pandemic for women and caregivers (Ahn et al., 2021; Malisch et al., 2020; Reese et al., 2021), universities have offered little guidance on how to teach and manage stress effectively (Gewin, 2021), and researchers feel busier (but less

productive) than pre-pandemic with little end in sight (De Gruyter, 2020). The pandemic has produced far-reaching effects across academia, but few studies have documented them from a psychological perspective, especially through large-scale analyses of text data.

If academia has indeed failed to adequately respond to the pandemic, researchers should not be immune to the psychological effects of the pandemic documented in other studies and settings. The pandemic and its consequences should therefore impact how academics behave, including how they write and what they focus on. Using field data from over 2.2 million academic papers across three studies, the current work identifies how the pandemic has systematically impacted researchers as revealed by their writing.

Managing Psychological Crises: A Tale of Two Thinking Modes

Crises and emotional upheavals often represent key moments in a person's life that change how they think and feel about the world. People who experience traumatic life events (e.g., the loss of a loved one, financial hardship, assault) often communicate in great detail about their encounters (Pennebaker, 1997; Pennebaker & Beall, 1986), suggesting language patterns can offer an important, natural lens into how people deal with distress.

Most research investigating psychological distress from a language perspective uses words to evaluate dynamics of the distress after it occurred (Markowitz & Hancock, 2017; Pavlacic et al., 2019; Rude et al., 2004; Stirman & Pennebaker, 2001). In such cases, a trauma or distress is identified and language cues (e.g., emotion) describe its psychological characteristics post-hoc, compared to a period of reduced distress. Therefore, a trauma is often finished upon its evaluation, leaving researchers with a limited understanding of the psychological processes involved as it unfolded or how people were thinking and feeling during the trauma. Only recent studies, such as those using social media text data, have evaluated the psychological aspects of

trauma *while communicators experienced* distress (Cohn et al., 2004; De Choudhury et al., 2016; Goolsby, 2010; Seraj et al., 2021). As a window into psychological processes, language is instrumental, offering an in-the-moment accounting of daily life experiences.

How do people communicate during a crisis or distressing life event? One of the most common approaches is to evaluate the thinking style of those experiencing trauma, which include two modes: analytic thinking and cognitive processing (Seraj et al., 2021). For example, Seraj and colleagues collected reddit texts related to romantic breakups and observed less analytic thinking and more words indicating cognitive processes were associated with the period after a breakup, returning to baseline weeks later.

Analytic thinking is identified via function words (e.g., articles, pronouns), which indicate *how* a person is communicating instead of *what* they are communicating about (Chung & Pennebaker, 2007). High scores on an analytic thinking index, established by Pennebaker et al. (2014), include positive loadings for articles (e.g., *the, a*) and prepositions (e.g., *above, below*), but negative loadings for pronouns (e.g., *I, she*), auxiliary verbs (e.g., *been, does*), conjunctions (e.g., *and, or*), adverbs (e.g., *briefly, finally*), and negations (e.g., *nor, not*). Writing that scores high on this measure is often “cold,” “dispassionate,” or impersonal compared to writing that scores low on this measure (Seraj et al., 2021). Analytic thinking is an important marker of various psychological processes and individual differences, including persuasion (Markowitz, 2019, 2020), cultural trends in politics (Jordan et al., 2019), and gender in entertainment speeches (Meier et al., 2020). Prior work has also used analytic thinking to indicate how members of the World Health Organization appraised rising COVID-19 cases and deaths over time (Markowitz, 2021). Together, the analytic thinking index “can be applied to any type of text” to signal the formal and impersonal nature of a writer’s communication style (high on

analytic thinking) or the informal and personal nature of a writer's communication style (low on analytic thinking) (Pennebaker et al., 2014, p. 6).

The second thinking mode considers words reflecting cognitive processes. These words often indicate a person “working through” a psychological issue or event (Boyd et al., 2020; Vine et al., 2020). Individuals who try to make meaning from a personal distress often express a high rate of cognitive processing words (e.g., *admit, depend, should*) compared to individuals who are not experiencing distress, which suggests the difficult work people put in to psychologically organize their thoughts during a traumatic time. Cognitive processing words have signaled the meaning-making process in settings such as romantic breakups (Seraj et al., 2021), national crises (e.g., terrorist attacks) (Cohn et al., 2004), and health crises (Pennebaker & Lay, 2002), when people typically experience heightened psychological distress.

Emotion. How people manage trauma is critical, and while the prior thinking modes describe the ways people cognitively handle crises via language, emotion also plays a crucial psychological role (Barattucci et al., 2020; Slovic et al., 2002). When people describe trauma, they often communicate in emotional terms with more negative affect compared to those who do not experience trauma (Cohn et al., 2004; Koss & Kilpatrick, 2001; Seraj et al., 2021; Vine et al., 2020). Therefore, emotion is an important indicator of distress and is investigated in this work to indicate how people responded psychologically to the pandemic in real time.

The Current Work

Together, the prior language dimensions — emotion, analytic thinking, and cognitive processing — appear in a range of settings to reflect trauma and psychological distress (e.g., breakups reported on social media, terrorist attacks on personal blogs). Despite the pandemic's ongoing nature at the time of this writing and other investigations that typically perform

retrospective evaluations of trauma, it is theoretically reasonable to expect these language dimensions will also be relevant during crises facilitated by COVID-19. Should these dimensions matter to mark how academics psychologically managed the pandemic, such evidence would support the idea that there are general psychological characteristics and meaning-making processes that can span traumas or distressing events over time.

The primary interest of this paper is to identify how academics responded to and worked through the pandemic as indicated by their writing. This untested empirical question also supports a tacit second aim: to replicate and extend prior research on communicating about trauma via language patterns (Cohn et al., 2004; Seraj et al., 2021). The language markers in this study are drawn from such prior work, making the current paper a conceptual replication to test how crises are reflected in language patterns of distress during the COVID-19 pandemic.

Papers written in a time of psychological distress should contain more affect (e.g., more negative emotion), more cognitive processing words, and a lower rate of analytic thinking than those written before the distress (Cohn et al., 2004; Seraj et al., 2021). Therefore, the pandemic and its effects should modify what researchers focus on and how they write their science. The prior language dimensions were preregistered on the Open Science Framework (<https://osf.io/t38kh/>), which also contains data and code. The link between *time* (pre-pandemic vs. peri-pandemic¹) and positive emotion was exploratory given its mixed connection to how people manage trauma (Chu et al., 2016; Fredrickson et al., 2003; Weiss et al., 2020).

Study 1: Method

The first study extracted all available abstracts and article metadata (e.g., authors, update

¹ “Peri” is a prefix describing a time “during” an event. Since the pandemic was ongoing at the time of data collection and this writing, “peri” is used instead of “post.” The terms “peri-pandemic” and “during pandemic” were used interchangeably for clarity at different points in the paper.

date of the paper) from arXiv.org² in April 2021. arXiv is a public repository of preprint research articles (Citron & Ginsparg, 2015), often representing the fields of physics, mathematics, computer science, quantitative biology, quantitative finance, statistics, electrical engineering and system science, and economics. arXiv was the chosen database for this first study because preprints contain language patterns that can approximate how the authors were thinking or feeling when they wrote a public version of a paper (before any potential edits during the peer review process). This database also has the advantage of scale, including a large collection of papers written before and during the COVID-19 pandemic for a comparison.

The first known or reported case of COVID-19 occurred on November 17, 2019 (Davidson, 2020; Roberts et al., 2021) and therefore, a conservative benchmark was created to identify papers published before ($n = 1,522,699$; before or on November 17, 2019) and during ($n = 320,022$; after November 17, 2019) the pandemic. To identify when papers were published, paper update dates were extracted from the abstract metadata. Therefore, abstracts written during the pandemic were compared to a set of control abstracts written before the pandemic, to first establish the idea that language patterns of trauma and emotional upheaval differ over time.

Further, arXiv identified COVID-19-specific articles in its database by searching the title and abstract of a paper for three terms: “COVID-19,” “SARS-CoV-2”, and “coronavirus.” At least one of these terms was present in the title or abstract for arXiv to identify it as a COVID-19 paper. In this first study, to isolate the genuine effect of *time* on language patterns that is unrelated to COVID-19 itself, COVID-19-specific papers identified by arXiv were excluded.

Non-English abstracts were removed (Ooms, 2020), and those < 25 words were excluded based on best practices for analyzing text data (Boyd, 2017). The final dataset contained

² <https://www.kaggle.com/Cornell-University/arxiv>

1,842,721 arXiv abstracts covering 262,977,712 words (Table 1 lists a summary of each sample).

Automated Text Analysis

All texts in this paper were analyzed with Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al., 2015). LIWC is an automated text analysis tool that counts words as a percent of the total word count per text, and counts a variety of social (e.g., words related to family), psychological (e.g., emotion terms), and part of speech categories (e.g., pronouns, articles, auxiliary verbs). For example, the sentence “Masks are helpful against COVID-19” contains 6 words and increments categories such as prepositions (e.g., *against*; 16.67% of the total word count) and positive emotion terms (e.g., *helpful*; 16.67% of the total word count). LIWC dimensions have been successfully applied to many analyses of science texts, from fraudulent science writing style patterns (Markowitz & Hancock, 2016) to persuasion in grant abstracts (Markowitz, 2019), and its dictionaries are validated across many settings (Boyd & Pennebaker, 2015; Boyd & Schwartz, 2021; Markowitz et al., 2021; Tausczik & Pennebaker, 2010).

LIWC dimensions. Five language dimensions were evaluated with LIWC: affect (e.g., *happy*, *hate*), positive emotion (e.g., *relieve*, *strong*), negative emotion (e.g., *risk*, *victim*), cognitive processes (e.g., *inform*, *question*), and analytic thinking. All variables are percentages of the total word count except for analytic thinking, which is a composite measure of function words ranging from 0, or low analytic thinking, to 100, or high analytic thinking. The formula³ for this composite produces a normalized score that can be compared across a range of texts.

A correlation matrix of the key LIWC variables is in Supplementary Table S1 and descriptive statistics are offered in Supplementary Table S2.

Study 1: Results and Discussion

³ Analytic thinking = [articles + prepositions - pronouns - auxiliary verbs - adverb - conjunctions - negations] from LIWC scores (Jordan et al., 2019).

Pilot Study

Prior work suggests academic abstracts can reflect the general language patterns of scientist (Markowitz, 2019; Markowitz & Shulman, 2021; Martínez & Mammola, 2021; Plavén-Sigray et al., 2017; Rains et al., 2020). To validate this idea in the current paper, however, a random sample of 50 arXiv articles and their associated abstracts were extracted. If abstracts offer a consistent linguistic signal as full papers, the same language dimensions for the abstract and paper should be significantly and positively correlated.

Bivariate correlations between the abstract text and full paper text were computed for the five language dimensions in this study: affect ($r = .636, p < .001$), positive emotion ($r = .516, p < .001$), negative emotion ($r = .848, p < .001$), cognitive processes ($r = .239, p = .039$), and analytic thinking ($r = .351, p = .013$). Indeed, academic abstracts reflect the language patterns of a full paper and how authors generally write.

Data Analysis Plan

Linear mixed models evaluated the relationship between *time* (pre-pandemic vs. peri-pandemic) and language patterns, controlling for the author who submitted the paper and the paper's primary subfield as random intercepts (Bates et al., 2015). Authors who submitted the arXiv preprint were often lead authors, which suggests they likely contributed much of the writing. Controlling for author as a random intercept accounted for any data non-independence and individual differences in writing style. Controlling for the paper's primary subfield, as identified by the article metadata, accounted for any systematic relationship between COVID-19 and writing style conventions between subfields. Full mixed model outputs are available in Supplementary Tables S4-S8.

arXiv Analysis

The relationship between *time* (pre-pandemic vs. peri-pandemic)⁴ and affect was positive and statistically significant ($B = 5.72\text{E-}02$, $SE = 4.05\text{E-}03$, $t = 14.14$, $p < .001$, $R^2c = 0.21$)⁵.

Therefore, affect was significantly higher peri-pandemic compared to pre-pandemic. This effect was replicated for both positive ($p < .001$, $R^2c = 0.15$) and negative emotion terms ($p < .001$, $R^2c = 0.22$). *Time* was marginally and positively associated with cognitive processing terms ($p = .057$, $R^2c = 0.25$), but not significantly associated with analytic thinking ($p = .271$, $R^2c = 0.15$) after controlling for submitting author and subfield. Taken together, emotion provides the most stable signal of the pandemic's effects compared to cognition, as revealed by word patterns.

Figure 1 displays smoothed trends over time across all language variables of interest, 1 year pre-pandemic (November 17, 2018) and 1 year peri-pandemic (November 17, 2020). The data suggest a relatively linear upward trend in emotion over time. Rates of cognitive processes and analytic thinking vacillated pre-pandemic but were comparatively more consistent during the pandemic. It is important to interpret these figures with caution, however, since the y-axes are constrained, and large visual differences are often quantitatively small. Data in Supplementary Table S3 also reveal little evidence of curvilinearity in these data after segmenting time.

This first study establishes the idea that writing during (versus before) the pandemic is linked to psychological trauma and emotional upheaval as reflected by word patterns. Papers written during the pandemic contained more emotion, including negative affect, than pre-pandemic papers. This evidence replicates prior work that used language to identify crises and traumas (Cohn et al., 2004; Pavlacic et al., 2019; Pennebaker, 1997, 2011; Seraj et al., 2021).

There are several items that should be addressed in another investigation, however. Chief

⁴ In all analyses, “pre-pandemic” was the reference group (see supplement). When a main effect of *topic* (COVID-related vs. non-COVID-related) was evaluated in Studies 2 and 3, “non-COVID-related” was the reference group.

⁵ R^2c represents variance explained by the fixed and random effects in linear mixed models from the MuMIn package in R (Bartón, 2020)

among them is that preprints are not the final representation of a research article and the writing in a paper might undergo substantial changes in peer review. Feedback during this process can substantially alter how the authors think about their science (e.g., their perspective can change after taking a step back from the paper) and then, how a paper is written (Park et al., 2016).

Therefore, published articles should also be evaluated to account for writing modifications that occur within a review cycle. It is also unclear how papers written specifically about the pandemic and its effects compare to those written not about pandemic topics. The theory supporting Study 2, based on prior literature (Cohn et al., 2004; Seraj et al., 2021), suggests writing *about* a trauma is associated with different psychological dynamics than not writing about a trauma. For example, writing about the terrorist attacks of September 11th as they occurred should be associated with a range of psychological experiences that could not be approximated by (or could be reduced by) writing about the attacks weeks later or not writing about them at all (Cohn et al., 2004; Fredrickson et al., 2003). This prediction is also supported by expressive writing research that suggests people who describe psychologically distressing events tend to have a different linguistic profile compared to those who describe non-distressing events (Pennebaker & Beall, 1986; Smyth, 1998; Travagin et al., 2015).

Study 2: Method

The next study addresses the shortcomings of Study 1 by evaluating language patterns before and during the pandemic, plus language effects by *topic* (related to COVID-19 or not). Abstracts from Public Library of Science (PLOS) One were collected in April 2021. This journal was chosen because of its high publication rate of COVID-19 papers and its systematic archiving of article metadata. Papers about COVID-19 ($n = 1,179$) were identified by the journal (e.g., via their curated collections) and compared to a control group of non-COVID-19 papers ($n =$

73,565). Papers were included in the control group if published within the past 5 years (since May 2016). Abstract text and metadata were collected (e.g., lead author, date of publication).

Consistent with Study 1, a conservative benchmark for the main effect of *time* was created to identify papers published before ($n = 71,709$; before or on November 17, 2019) and during ($n = 3,035$; after November 17, 2019) the pandemic. Note, since papers in PLoS One's curated COVID-19 archive did not contain papers before November 17, 2019 at the time of data collection, a Topic (COVID-related vs. not COVID-related) $\times$ Time (pre-pandemic vs. peri-pandemic) interaction was not computed in this study. Only the main effects of *time* and *topic* were evaluated concurrently in Study 2's statistical models.

After excluding abstracts with < 25 words and those with unextractable text, the final dataset included 74,744 abstracts (19,220,877 total words). A correlation matrix of the key LIWC variables is in Supplementary Table S9 and descriptive statistics are offered in Supplementary Table S10.

Study 2: Results and Discussion

Pilot Study

Consistent with Study 1, bivariate correlations between a random selection of 550 PLoS One COVID-19 abstracts (nearly half of the available COVID-19 papers from the journal) and full texts were computed for affect ($r = .786, p < .001$), positive emotion ($r = .745, p < .001$), negative emotion ($r = .827, p < .001$), cognitive processes ($r = .631, p < .001$), and analytic thinking ($r = .506, p < .001$). Abstracts from PLoS One therefore offer a reliable signal of the authors' general writing style.

Data Analysis Plan

Study 2 followed the same data analysis plan as Study 1 by assessing the effects with

linear mixed models, controlling for first author of the paper (subfield was unavailable in the paper metadata). Main effects of *time* and *topic* were evaluated simultaneously in each model. Full model outputs are in the online supplement (see Supplementary Tables S11-S15).

PLoS One Analysis

Papers written during the pandemic ($B = 1.30\text{E-}01$, $SE = 4.28\text{E-}02$, $t = 3.05$, $p = .002$, $R^2c = 0.27$) and those about COVID-19 ($B = 4.66\text{E-}01$, $SE = 6.80\text{E-}02$, $t = 6.86$, $p < .001$) contained more emotion than papers written before the pandemic and those not about COVID-19. Specifically, papers written during the pandemic contained more positive affect ($p = .016$, $R^2c = 0.27$) after controlling for *topic*, which was not significant ($p = .258$). Papers written about COVID-19 contained more negative affect ($B = 3.91\text{E-}01$, $SE = 5.07\text{E-}02$, $t = 7.71$, $p < .001$, $R^2c = 0.26$) after controlling for *time*, which was marginally significant and positive ($p = .096$).

Regarding cognition and thinking styles, papers written about COVID-19 ($B = -2.60\text{E-}01$, $SE = 1.15\text{E-}01$, $t = -2.26$, $p = .024$, $R^2c = 0.30$) contained a lower rate of cognitive processing terms after accounting for *time*, which was not significant in the model ($p = .464$). Papers written about COVID-19 ($B = 2.91\text{E-}01$, $SE = 1.08\text{E-}01$, $t = 2.69$, $p = .007$, $R^2c = 0.20$) contained a greater rate of analytic thinking after accounting for *time*, which was not significant in the model, either ($p = .241$).

Taken together, writing during the pandemic and specifically about COVID-19 associates with more verbal changes to emotion than cognition (compared to writing before the pandemic and not about COVID-19 topics). One concern with this study, however, is that the evidence originates from a single journal and therefore, the results may not generalize to other outlets. Examining a more diverse dataset would help to identify if the reported language patterns hold or are specific to this general interest outlet. The number of COVID-19 papers was also small in

PLoS One versus the number of papers unrelated to COVID-19. Study 3 addresses such limitations and seeks to evaluate the prior effects in a broader sample. The larger and more temporally diverse dataset in Study 3 also facilitated a crucial Topic (COVID-related vs. not COVID-related) $\times$ Time (pre-pandemic vs. peri-pandemic) interaction to evaluate the joint impact of writing about COVID-19 during the pandemic compared to writing about other topics at other time points.

Study 3: Method

The COVID-19 Open Research Dataset (CORD-19) contains articles and abstracts on “COVID-19, SARS-CoV-2, and related coronaviruses.” The data were obtained from a public repository in April 2021 (Wang et al., 2020)⁶. This dataset was compiled by the Allen Institute for AI, The White House Office of Science and Technology Policy, the National Library of Medicine, the Chan Zuckerberg Initiative, Microsoft Research, and Kaggle. It is specifically aimed at the academic research community to “apply recent advances in natural language processing and other AI techniques to generate new insights in support of the ongoing fight against this infectious disease.” Consistent with this aim, Study 3 investigated how writing during the pandemic (and about COVID-19) is associated with markers of psychological change compared to writing before the pandemic (or about other topics).

Note, while this dataset contains many papers related to COVID-19 and coronaviruses, it also contains papers related to biological processes that might be affected by COVID-19 and other coronaviruses (e.g., the respiratory system). Therefore, the collection contains papers directly and indirectly related to COVID-19.

⁶ <https://www.kaggle.com/allen-institute-for-ai/CORD-19-research-challenge>

Like Study 2, the same approach to identify papers that were published before or during the COVID-19 pandemic was adopted. Article publication dates were extracted from the paper metadata and a benchmark was created to identify papers published before ($n = 76,681$; before or on November 17, 2019) and during ($n = 284,508$; after November 17, 2019) the pandemic⁷. Papers were also identified as relating to COVID-19 if their abstracts contained the terms “COVID-19,” “SARS-CoV-2,” or “coronavirus.” The effect of *topic* (COVID-related $n = 214,551$ vs. not COVID-related $n = 146,638$) was evaluated concurrently with *time*.

After excluding duplicates, abstracts with < 25 words (Boyd, 2017), abstracts not written in English (Ooms, 2020), and papers with incomplete metadata, the final dataset included 361,189 abstracts from largely published papers (76,782,968 total words).

A correlation matrix of the key LIWC variables is in Supplementary Table S16 and descriptive statistics are offered in Supplementary Table S17.

Study 3: Results and Discussion

Pilot Study

Consistent with Studies 1 and 2, bivariate correlations between a random selection of 50 abstracts and full paper texts were computed using the CORD-19 sample for affect ($r = .531, p < .001$), positive emotion ($r = .454, p < .001$), negative emotion ($r = .582, p < .001$), cognitive processes ($r = .488, p < .001$), and analytic thinking ($r = .481, p < .001$). These significant associations ensured that abstracts provide a consistent and reliable signal as full papers.

Data Analysis Plan

Study 3 followed the same data analysis plan as Study 2 by assessing the effects with

⁷ In some cases, only a year of publication was provided in the article metadata. To remain conservative with the estimate of papers published before or during the pandemic, any paper labeled “2019” was placed in the “before” group of the *time* factor. Any paper labeled “2020” or later was placed in the “during” group of the *time* factor.

linear mixed models, controlling for first author of the paper (subfield was unavailable in the paper metadata). *Time* and *topic* were evaluated simultaneously in the mixed models for each language dimension, followed by Time $\times$ Topic interactions. Full model outputs are in Supplementary Tables S18-S22.

CORD-19 Analysis

Papers written during the pandemic ($B = 5.36\text{E-}01$, $SE = 1.02\text{E-}02$, $t = 52.38$, $p < .001$, $R^2c = 0.62$) and those about COVID-19 ($B = 1.91\text{E-}02$, $SE = 8.40\text{E-}03$, $t = 2.27$, $p = .023$) contained more emotion than papers written before the pandemic and those not about COVID-19. Specifically, papers written during the pandemic contained more positive affect ($p < .001$, $R^2c = 0.62$) after controlling for *topic*, which was significant and negative in the model ($p < .001$). Papers written during the pandemic also contained more negative affect ($p < .001$, $R^2c = 0.59$) after controlling for *topic*, which was significant and positive in the model ($p < .001$).

Papers written during the pandemic ($B = 4.99\text{E-}01$, $SE = 1.51\text{E-}02$, $t = 33.00$, $p < .001$, $R^2c = 0.59$) contained a greater rate of cognitive processing terms after accounting for *topic*, which was significant in the model and negative ($p < .001$). Papers written during the pandemic ($B = -3.07\text{E-}01$, $SE = 1.98\text{E-}02$, $t = -15.50$, $p < .001$, $R^2c = 0.54$) contained a lower rate of analytic thinking after accounting for *topic*, which was significant in the model and positive ($p < .001$). Therefore, after accounting for paper topic (COVID-19 or not), scientists writing during the pandemic tend to have a less analytic style and display greater evidence of “working through” issues than scientists writing before the pandemic.

CORD-19: Interaction of Topic and Time

Five separate Topic (COVID-related vs. not COVID-related) $\times$ Time (pre-pandemic vs. peri-pandemic) interaction effects — one for each language dimension (e.g., affect, positive

emotion, negative emotion, cognitive processes, analytic thinking) — were computed using a mixed effects regression. Each model contained a random intercept for lead author of the paper.

Affect. Topic $\times$ Time interactions were significant for affect [$F(1, 342941) = 321.99, p < .001$], positive emotion [$F(1, 341521) = 57.38, p < .001$], and negative emotion [$F(1, 348075) = 271.46, p < .001$]. Figure 2 and Table 2 display the joint impact of writing during the pandemic and specifically about COVID-19. For example, the rate of negative emotion before the pandemic was equivalent for COVID-19 and non-COVID-19 papers. During the pandemic, COVID-19 papers contained more negative affect than non-COVID-19 papers, suggesting potential psychological consequences of researching and writing in this time (e.g., more focus on a negative emotional state).

Cognitive processes and analytic thinking. As the bottom panels of Figure 2 reveal, a Topic $\times$ Time interaction was significant for cognitive processes [$F(1, 347401) = 31.05, p < .001$], but not analytic thinking [$F(1, 354063) = 0.08, p = .777$]. All pairwise comparisons across language variables are reflected in Table 2.

Classification Accuracy

How well do the five language features classify *time* (pre-pandemic vs. peri-pandemic) and *topic* (COVID-19 vs. non-COVID-19 papers) in Study 3? Classification accuracies were assessed using Area Under the Receiver Operating Characteristics (ROC) Curve models.

Time. Classification accuracies for all variables, including affect (0.587), positive emotion (0.564), negative emotion (0.545), cognitive processes (0.520), and analytic thinking (0.501), were above chance (0.500) to predict *time* peri-pandemic. As a composite variable⁸,

⁸ Two composite variables were calculated by standardizing each variable and then applying weighted formulas depending on the main effect results of time or topic. For *time* analyses, the following formula was applied: Affect + Positive emotion + Negative emotion + Cognitive processes – Analytic thinking. For *topic* analyses, the following formula was applied: Affect + Negative emotion + Analytic thinking – Cognitive processes – Positive emotion.

classification accuracy was relatively stable (0.578).

Topic. The ROC analysis for negative emotion (0.564), affect (0.541), and analytic thinking (0.516) were above chance (0.500) to predict a COVID-19 paper, but positive emotion (0.494) and cognitive processes (0.472) were below chance. As a composite variable, the ROC model accuracy (0.565) was stable as well. Taken together, just by counting words, pre-pandemic papers can be distinguished from pre-pandemic papers with a small, but theoretically meaningful amount of classification accuracy.

General Discussion

The COVID-19 pandemic has generated a range of psychological consequences for populations around the world. Average citizens are suffering intense mental health crises, financial uncertainties, and health concerns that feel unrelenting. The current paper finds evidence that the pandemic has impacted academic research communities in systematic, nontrivial ways as indicated by language patterns. Results from this paper suggest scientists writing about COVID-19 tend to have an increased focus on affect, specifically negative emotion, in preprint papers from arXiv (Study 1) and published work (Studies 2 and 3).

It is important to speculate why some consistencies emerged across studies (e.g., the overall emotion effects) and why inconsistencies emerged for analytic thinking and cognitive processing. Perhaps the emotion effects largely replicated across studies because emotion might be a more stable psychological dynamic than how people think about a trauma (e.g., via cognitive processes, which indicate people working through a crisis). The degree to which people are trying to work through an issue might be more flexible or affected by contextual elements (e.g., the writing style conventions of a journal). Psycholinguistics research suggests communicators often belong to a range of discourse communities (Biber et al., 2007), which

shape how people talk or write in order to meet the expectations of the audience. For example, academics write differently to their significant others than they do to their students because the audience and their expectations are dissimilar. A related argument can be made for academic journals because authors often attempt to meet the expectations of a journal and its readers, shifting their writing style to meet the norms or conventions of the journal's genre and the context (see Markowitz & Hancock, 2019). PLoS One, a general interest journal, might have a distinct set of conventions compared to other journals and therefore, the differences in Study 2 (relative to Study 1 and Study 3) might reflect writers attempting to meet such expectations. When more diverse journals are included (Study 3), the impact of such conventions might be reduced or suppressed. Future work should test how the genre, journal conventions, and other contextual characteristics affect how authors write during crises.

Another possibility is the idea that psychological distress is processed via dual pathways where emotion operates independently of cognition in cases of meaning-making and handling trauma. Emotion may be heightened during a period of distress, pervading how people think and feel about a particular event (e.g., a trait-like dynamic that might be enduring throughout a trauma). Cognition, on the other hand, may be more malleable (e.g., a state-like dynamic possibly affected by contextual elements such as journal conventions). Future work should test the possibility that trauma is reflected via different psychological pathways and context-specific characteristics (e.g., journal or genre conventions, plus audience expectations).

Together, there are several contributions of this research worth highlighting. First, this paper used large-scale text data (over 2.2 million observations and over 350 million words) from natural settings to identify how academics and researchers responded to trauma in real time. Computational approaches to text analysis were instrumental in quantifying such a large number

of academic texts, adding to a tradition of research that uses automated methods to count words at scale and indicate psychological processes (Boyd & Pennebaker, 2015; Boyd & Schwartz, 2021; Pennebaker, 2011). These data were collected in an unobtrusive manner, which allowed for communication patterns to occur naturally over time. Across topics of research and circumstances that might be affecting authors' writing differentially, language still revealed a systematic pattern that describes how scientists psychologically responded to the COVID-19 pandemic. These effects demonstrate the power of language as a window into how people are thinking and feeling in a complex, challenging, and changing world.

This paper also contributes to our understanding of psychological distress, trauma, and emotional upheaval. It is often difficult to measure distress as it occurs and most research uses post-hoc evaluations of trauma to indicate how people handled such experiences. This work demonstrates in-the-moment evaluations of trauma and emotional upheavals are reflected in language patterns and indicate how scientists make meaning of their experiences. Writing about trauma, as one experiences it, is indeed associated with a different psychological experience than not writing about trauma or writing during a period of distress but not experiencing it oneself.

Taken together, this paper supports a growing body of work that uses computational approaches to understand psychological phenomena in the field, particularly from language patterns. There are many techniques to automatically count words and make sense of language in the social sciences (Kennedy et al., 2021), yet few studies have examined how trauma unfolds in real time with naturally occurring data, much less using scientists as a lens into psychological functioning. It is more typical for scientists to evaluate others instead of turning a psychological mirror inward. This work argues and provides evidence that much can be learned by focusing on language patterns and investigating how scientists communicate during times of distress.

Stakeholders in academe need to take the psychological health and well-being of researchers seriously during the pandemic. Even journal publications, which style guides suggest should report on science objectively and unemotionally, indicate psychological distress and emotional upheaval. Researchers and university faculty are often expected to “have it together;” these data suggest many are struggling and such issues are revealed in their work. Perhaps institutional guardrails can be implemented, including mental health resources and clear job expectations, to assist during the pandemic as its effects might be long-lasting.

Limitations and Future Directions

There are several considerations for future work and limitations that should be resolved. First, this paper did not measure how much authors experienced direct or indirect trauma due to COVID-19. Instead, it relied on the assumption that the pandemic has created a variety of social, cognitive, and institutional stressors that can impact how people function psychologically. This paper’s preregistration articulated language dimensions that should be associated with experiencing trauma based on prior work, and many patterns received support. Trauma appears to have general linguistic traces inside and outside a pandemic. Therefore, while trauma and its severity were not measured directly, it was reflected and indicated by word patterns that are typical of trauma. This is an assumption in most psychology of language papers (Boyd & Schwartz, 2021; Markowitz & Shulman, 2021), one that has been substantiated in many studies (Boyd & Pennebaker, 2015; Boyd & Schwartz, 2021; Tausczik & Pennebaker, 2010).

Second, the effect sizes in this paper were small. Effect sizes for language patterns are often within the ranges reported here (Kern et al., 2014; Kramer et al., 2014; Markowitz & Shulman, 2021), but it is worth noting that the studies benefited from having a large number of cases to identify such effects. The results are still theoretically meaningful, however, because

they demonstrate that trauma and emotional upheaval appear in the writing of academic papers, which are expected to report unemotionally and objectively on science. Small effects, when scaled at the field or discipline level across a high volume of writers, still suggest many academics are likely displaying psychological consequences of the pandemic in their work.

Relatedly, the patterns reported in this research are not direct cause and effect. According to Boyd and Schwartz (2021), “word frequencies represent attentional habits” (p. 24). Therefore, if a person uses high rates of negative emotion words in their writing, this does not suggest the person necessarily *experienced* these emotions nor has COVID-19 *caused* an increase in negative affect. Instead, the high rate of negative emotion words would typically reflect one’s *attention toward* a negative affective state. It is important for future work to identify the authors who experienced versus attended to emotional states, and if this difference modifies effects reported in this paper. Future research should also consider using experimental approaches, with scientists as participants, to evaluate how experiencing distress changes academic writing patterns.

It is unclear if the language patterns reflected here are also useful to prospectively identify authors who are experiencing or focusing on psychological states as a result of trauma. The classification accuracies in Study 3 were low, but LIWC’s word counting approach is simple. With more sophisticated word counting and classification techniques, plus the inclusion of more language dimensions, classification accuracy should improve. It might then be possible to use language patterns to identify distress from science papers, possibly serving as warning signs to indicate scholars who are experiencing particularly adverse pandemic effects.

I speculated that the difference in certain language patterns between studies occurred because of shifting genre conventions across journals. The expectations of a journal’s audience can facilitate changes to the authors’ writing style and psychological focus. To test this

contention, future research should try to collect papers from journals with distinct conventions to evaluate how such contextual elements affect writing patterns. Another possible explanation for the results, in general, is the idea that COVID-19 became a shared trauma over time. Therefore, as the pandemic progressed, writing styles may have shifted as people learned how to cope or rely on others for support, which changed their psychological focus and attention. Third, these results might also reflect a general change in cultural thinking that is being reflected by scientists. Future research should attempt to tease apart these alternative explanations.

Finally, while many effects in this paper were consistent with those from other research evaluating trauma on social media or blogs, academic papers are qualitatively different. Social media and blogs likely contain more personal references and stories compared to academic papers, which are more impersonal by nature. Future work should evaluate how such contextual elements of a setting might impact language patterns as well.

Conclusion

Evaluations of trauma and emotional upheaval tend to focus on ordinary citizens and use unstructured text to indicate how they psychologically managed a crisis. The current paper suggests consistent meaning-making processes occur for researchers at the language level of science abstracts. Academics who wrote about and during COVID-19 tended to focus on affect more than academics who wrote about other topics and pre-pandemic. Language is therefore an important tool to understand how people manage and cognitively work through trauma.

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Table 1*Descriptive Summary Across Studies and Samples*

Study and sample	<i>N</i>	Word count	
		<i>M</i>	<i>SD</i>
Study 1: arXiv	1,842,721	142.71 words	66.18 words
Study 2: PloS One	74,744	257.16 words	66.82 words
Study 3: CORD-19	361,189	212.58 words	92.80 words

Table 2*Interaction Effect Pairwise Comparisons Across Language Dimensions: Study 3*

Study 3	Group 1	Group 2	Estimate	SE	z-ratio	p
Affect	COVID-related, pre-COVID	Not COVID-related, pre-COVID	-0.35	0.02	-15.74	< .001
	COVID-related, pre-COVID	COVID-related, peri-COVID	-0.88	0.02	-40.46	< .001
	COVID-related, pre-COVID	Not COVID-related, peri-COVID	-0.80	0.02	-35.55	< .001
	Not COVID-related, pre-COVID	COVID-related, peri-COVID	-0.53	0.01	-54.68	< .001
	Not COVID-related, pre-COVID	Not COVID-related, peri-COVID	-0.45	0.01	-40.42	< .001
	COVID-related, peri-COVID	Not COVID-related, peri-COVID	0.08	0.01	8.78	< .001
Positive emotion	COVID-related, pre-COVID	Not COVID-related, pre-COVID	-0.33	0.02	-21.10	< .001
	COVID-related, pre-COVID	COVID-related, peri-COVID	-0.54	0.02	-35.32	< .001
	COVID-related, pre-COVID	Not COVID-related, peri-COVID	-0.74	0.02	-46.79	< .001
	Not COVID-related, pre-COVID	COVID-related, peri-COVID	-0.21	0.01	-30.98	< .001
	Not COVID-related, pre-COVID	Not COVID-related, peri-COVID	-0.41	0.01	-52.41	< .001
	COVID-related, peri-COVID	Not COVID-related, peri-COVID	-0.20	0.01	-31.60	< .001
Negative emotion	COVID-related, pre-COVID	Not COVID-related, pre-COVID	-0.01	0.02	-0.85	.829
	COVID-related, pre-COVID	COVID-related, peri-COVID	-0.31	0.02	-19.64	< .001
	COVID-related, pre-COVID	Not COVID-related, peri-COVID	-0.04	0.02	-2.39	.080
	Not COVID-related, pre-COVID	COVID-related, peri-COVID	-0.30	0.01	-42.23	< .001
	Not COVID-related, pre-COVID	Not COVID-related, peri-COVID	-0.03	0.01	-3.13	.010
	COVID-related, peri-COVID	Not COVID-related, peri-COVID	0.27	0.01	41.53	< .001
Cognitive processes	COVID-related, pre-COVID	Not COVID-related, pre-COVID	-0.72	0.03	21.91	< .001
	COVID-related, pre-COVID	COVID-related, peri-COVID	-0.66	0.03	-20.33	< .001
	COVID-related, pre-COVID	Not COVID-related, peri-COVID	-1.18	0.03	-35.28	< .001
	Not COVID-related, pre-COVID	COVID-related, peri-COVID	0.06	0.01	4.40	< .001
	Not COVID-related, pre-COVID	Not COVID-related, peri-COVID	-0.46	0.02	-27.79	< .001
	COVID-related, peri-COVID	Not COVID-related, peri-COVID	-0.52	0.01	-39.15	< .001
Analytic thinking	COVID-related, pre-COVID	Not COVID-related, pre-COVID	0.32	0.04	7.22	< .001
	COVID-related, pre-COVID	COVID-related, peri-COVID	0.30	0.04	6.91	< .001
	COVID-related, pre-COVID	Not COVID-related, peri-COVID	0.63	0.04	14.10	< .001
	Not COVID-related, pre-COVID	COVID-related, peri-COVID	-0.02	0.02	-1.03	.734
	Not COVID-related, pre-COVID	Not COVID-related, peri-COVID	0.31	0.02	14.24	< .001
	COVID-related, peri-COVID	Not COVID-related, peri-COVID	0.33	0.02	18.72	< .001

Note. *P*-values were adjusted using Tukey's method. Degrees of freedom were calculated using the asymptotic method.

Figure 1

Visualized Trends in Language Patterns Over Time (Study 1)

Note. Dashed lines represent November 17, 2019, or when the first COVID-19 case was reported. These data reflect trends 1-year before and after November 17, 2019. Trend-lines were smoothed using the Generalized Additive Method in R.

Figure 2

Interaction effects of Topic (COVID-related vs. not COVID-related) $\times$ Time (Pre-pandemic vs. Peri-pandemic)

Note. Error bars are 95% Confidence Intervals. These data control for first author as a random intercept in the linear mixed models.