Computing Vulnerability: Recommendations for Supporting the Emotional Wellbeing of Computational Researchers

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Abstract

Increasingly, researchers conducting computational analysis of online communities conduct emotionally demanding research. Recently, the broader academic community has begun to identify the negative impact of emotionally demanding research on qualitative researchers exposed to sensitive content when researching vulnerable populations, and has begun to determine best practices and guidelines to support the wellbeing of those researchers. However, there is a need to provide support for researchers conducting computational research in these areas as well. This paper presents an auto-ethnography describing the emotional duress one research team encountered during a computational linguistic analysis of an online community focused on providing suicide bereavement support. Reflecting on the emotional demands the research team experienced in this work, this paper identifies two illustrative areas of emotional demands computational researchers might encounter when researching vulnerable populations. Using these illustrative examples as a grounding point, this paper concludes by providing recommendations for how research teams conducting emotionally demanding computational research can improve their wellbeing during the research process.

Introduction

Computational analysis has proven to be a useful set of methods when researching communities where vulnerable populations are seeking support (Chancellor and De Choudhury 2020; Chancellor et al. 2021; De Choudhury et al. 2014). Valuable platform design recommendations have emerged from computational analysis researching communities supporting users around death, grief, harassment, domestic violence, and illness. Computational analysis provides an avenue to identify patterns at a large scale, deriving design recommendations based on a wide range of data points. For example, topic modeling and sentiment analysis algorithms are powerful tools that can quickly and efficiently describe linguistic features of massive datasets of social media posts.

Due to the high-level, wide-scale algorithm-basis of computational analysis, it may be easy to assume that a researcher using computational methods is 'protected' from emotional demand relative to their exposure to sensitive content. However, it is increasingly clear in emerging research that there *is* an emotional burden placed on computational researchers when conducting research on/with communities that contain posts including graphic or sensitive content (Chancellor et al. 2019). Recent work, such as a workshop presented by Feuston et al. at CHI 2022 (Feuston et al. 2022) and a study surveying bereavement researchers by Moncur (Moncur 2013), have begun to prioritize developing guidelines for researcher wellbeing when conducting emotionally demanding research. Though this work has made great strides toward bringing awareness to improving researcher wellness, the recommendations have largely been directed at improving wellness practices for qualitative research methods (Dickson-Swift et al. 2008). This paper argues that scholarship focused on establishing best practices and guidelines for conducting emotionally demanding research should increasingly consider the impact of emotionally demanding research on researchers conducting computational analysis. After all, creating an annotated data set and validating the results of analysis via close textual analysis are important aspects of computational research that necessarily involve a close relationship with the data. Expanding on important work that focuses on the potential of web data to capture the struggles and wellbeing of vulnerable populations, this paper turns inward toward how research communities like ICWSM can identify and implement practices that improve the wellbeing of computational researchers conducting emotionally demanding work.

To examine the impacts of emotionally demanding research on researchers conducting computational research – and to identify recommendations for improved practices – this paper presents an auto-ethnography using one research team as a case study. In this paper, I – the lead researcher of that team – present the results of an auto-ethnography on behalf of the team. This auto-ethnographic process occurred during a study in which we conducted a computational linguistic analysis of the r/SuicideBereavement subreddit (Doyle et al. 2024). Using our own story of the emotional impact we experienced during the computational linguistic study, I identify two illustrative areas of emotional demand that we experienced. Using these illustrative examples as a grounding point, I then provide several recommendations for potential avenues to improve wellbeing practices for research teams conducting emotionally demanding computational research. These areas of emotional demand and suggested ways forward are not comprehensive, but instead continue a conversation, providing a call to action for HCI communities like ICWSM to increasingly focus on improving the wellbeing needs of researchers conducting emotionally demanding computational research.

Related Work

HCI scholars have started to discuss practices and strategies to support researchers in carrying out emotionally demanding work (Moncur 2013; Wolters, Mkulo, and Boynton 2017; Dickson-Swift et al. 2008). This growing area of research identifies the need for more thoroughly developed guidelines and resources for research teams and institutions (Andalibi and Forte 2015, 2016; Kumar and Cavallaro 2018; Doyle and Brubaker 2023; Doyle, Brahm, and Brubaker 2024). Work in this area has predominantly focused on researcher wellbeing in conducting qualitative social computing research involving sensitive content posted to online communities that support vulnerable populations. For example, (Moncur 2013) has identified guiding considerations for practice in the form of a set of questions that research teams should ask when study planning. (Andalibi and Forte 2016) has added that the creation of a common community-level peer support space for researchers would be a useful next step for generating best practices – providing a space where personal stories can help create guidelines based on the lived experience of researchers. This influential work has catalyzed conversations across many different HCI areas. For example, (Wolters, Mkulo, and Boynton 2017) has expanded on earlier work in the eHealth space by highlighting how creating reflection mechanisms for research teams conducting eHealth research can improve research team wellbeing. However, efforts in the computational research community to create guidelines and resources are scant. While conversations about the emotional demands of research on online communities of vulnerable populations certainly occur informally between colleagues, more intentional conversations about improving researcher wellbeing are needed at the level of published scholarship. This paper extends previous work on qualitative researcher wellbeing by arguing that similar work should be prioritized in computational research spaces. This paper additionally brings visibility to a challenge that many communities like ICWSM informally discuss in passing: How do we improve the wellbeing of computational researchers who conduct emotionally demanding research?

Methods

This paper offers an auto-ethnographic reflection about the challenges our research team encountered throughout a recent study we conducted researching linguistic patterns on r/SuicideBereavement – an online suicide bereavement support community (Doyle et al. 2024). Our study sought to determine the linguistic features of narrative posts within r/SuicideBereavement and determine whether those linguistic features allow us to predict patterns of narrative expression in other grief support communities. To achieve these goals, we first qualitatively studied narrative posts and their corresponding comments. We surveyed and characterized the community, developed a codebook for coding posts, and manually tagged a subset of 'narrative' posts. We then conducted a computational analysis using multiple linguistic tools (VADER, Syuzhet, and LIWC). We compared key linguistic features across narrative posts, non-narrative posts, and their respective comments. Finding significant linguistic differences between narrative and non-narrative posts, we then constructed a machine-learning classification model to aid us in future narrative tagging at scale. We applied our model to additional posts from r/SuicideBereavement and, after validating its accuracy again through manual coding, noted the proportion of narrative posts compared to non-narrative posts. We then applied our model to a more general grief support community, r/GriefSupport, and validated that our model accurately tagged narrative in r/GriefSupport. We then determined the proportion of narrative posts compared to non-narrative posts in a substantial corpus of r/GriefSupport posts – demonstrating that our model can accurately tag narrative posts and generate insights across multiple grief contexts. The data collection for this study was conducted over five months, and the data analysis occurred over nine months.

While conducting the data collection and data analysis, the research team met bi-weekly. In these meetings, we discussed the challenges and results of our research. Early on in the research process, it became clear that engaging with suicide bereavement posts, both qualitatively and computationally, was taking a toll on the wellbeing of the members of the research team. Following the suggestion of (Moncur 2013) to formalize reflection to improve researcher wellbeing, we adapted our research process by adding 15 minutes to the end of each meeting to hold space for members to reflect on the emotional demand of the research and seek support from other members of the research team. The lead researcher led these conversations, being careful to frame the conversations as peer support and not therapy. Members of the research team made a collective choice to track the emotional challenges they experienced throughout the study and consented to high-level notes being taken summarizing these conversations. In each reflection session, research team members were prompted to reflect on if/how the research was impacting them emotionally, how that emotional impact influenced their relationship to the research, and what could be changed in the research process to reduce the negative emotional impact and improve their wellbeing. In this paper, I synthesize the major themes of the notes, including challenges and recommendations. To generate the themes, members of the research team reviewed the notes and identified the most salient takeaways – reported in this paper by the lead researcher on behalf of the team.

Methodologically, these notes are a form of auto-ethnographic data. Auto-ethnography is the creation of an ethnography focused on the self (Chang 2016). In auto-ethnography, the author adopts an objective stance to their personal experience and interprets their own actions, thoughts, and behavior. Auto-ethnography is an increasingly popular approach in HCI research, highlighting the importance of a first-person understanding of the technology at hand by using an individual's personal experience as research material (Gamboa 2022; Jain et al. 2019). Here, autoethnography is used to describe the emotional demands our research team experienced when conducting computational analysis.

Examining Emotional Demands: Symptoms and Causes

Ours was a 'successful' study that generated a machine-learning model to detect a linguistic signature that we believe can assist HCI researchers and practitioners in designing more effective support for a vulnerable population – in this case, people bereaved by suicide. However, during this research, the research team encountered emotional demands that required special attention to maintain our wellbeing. Similar to the experience of bereavement researchers surveyed by (Moncur 2013), individual research team members experienced periods of crying, feelings of guilt, bad dreams, and increased daily awareness of their own fears of death. When reflecting on the underlying emotional demands that caused these symptoms, we identified two main emotional demands: (1) content triggering trauma responses, and (2) guilt caused by ethical concerns that our computational analysis would not accurately reflect the intimate nuance of bereavement.

Content Triggering Trauma Responses

In reflection sessions, research team members expressed how the content of suicide bereavement posts caused them to relive their own past trauma. The lead researcher, for example, had recently lost a loved one to suicide prior to beginning the study. Although that loss was a motivating force to begin the study in the first place, manually reading through suicide bereavement posts inevitably forced them to reflect on their recent loss. For research team members, posts triggered memories of personal loss, leading to a hesitancy/fear in when manually tagging posts to train the model on.

Though re-triggering difficult memories of personal loss may be expected to a certain degree during reading and manually tagging of posts, more surprising to us was the re-triggering of personal trauma that occurred during computational sentiment analysis – even when we were not reading the posts or manually tagging the posts directly. When we began to conduct sentiment analysis, reflection sessions quickly turned to focus on talking about the nature of emotion during times of grief. The computational process of identifying and parsing emotion led to deeply personal conversations between research team members about their own losses, their fear of analyzing the losses of others, and discussions about how to navigate those triggers. Contrary to the myth that computational analysis creates a barrier of distance between the researcher and the emotional valence of the research subject matter, we experienced that our sentiment analysis methods actually triggered the same emotional demands as when manually tagging posts.

Guilt Caused by Ethical Concerns

In conducting computational analysis, we additionally experienced the emotional demand of guilt – fearing that the computational model we were constructing would misrepresent the lived experience of posters in this community.

We decided to use computational analysis in this study because we sought to build and validate a model that could support bereavement communities at a large scale. When building and validating this model, we often reflected on the ethics of building a big data model that tagged and captured the data of people who shared their intimate and intense stories of loss. As one researcher remarked, "Who are we to automate their grief without their permission?" Although we received the consent of the moderator leadership of the community to conduct this study, we struggled with the impossibility of obtaining the consent of the thousands of users on which our model was built. We also struggled with the degree to which such a model would be helpful for community users. As another researcher summarized, "Who's to say that the platform developer won't just use this model for monetization or to cause harm?"

How to address the ethical concerns of computational data collection is a live conversation among HCI scholars (Chancellor and De Choudhury 2020; Chancellor, Baumer, and De Choudhury 2019). In our case, the intimate stories of bereavement by community members heightened our senses to these concerns, causing us to question whether the computational outcome of this work was fundamentally unethical due to the vulnerability of the people in the community. These ethical concerns were not just intellectual concerns, but weighed heavily on the emotional wellbeing of the research team. Ultimately, we continued with the study, hoping that our model can and will be used to support vulnerable populations seeking grief support online. However, throughout the research process, the tension of ethical issues inherent in conducting computational analysis on the data of bereaved individuals caused immense emotional duress to research team members.

Considerations for Supporting Researcher Wellbeing

The examples of fear and guilt that our team experienced illustrate broader personal challenges that computational scholars conducting emotionally demanding research may encounter. Though these examples are not comprehensive, they provide auto-ethnographic data that speaks to a growing need for researchers using computational methods to receive additional support when studying online communities of vulnerable populations. We should not assume that just because computational analysis does not always involve qualitatively reviewing every piece of data, computational researchers do not require improved support for their wellbeing.

To attempt to improve the wellbeing of our own research team, after we realized that our research was taking an emotional toll, we consulted Moncur's paper identifying ways in which research teams using qualitative methods can proactively incorporate consideration for the emotional wellbeing of researchers into the research process itself (Moncur 2013). Moncur suggests that research teams conducting emotionally demanding research should consider (1) the potential risks to the researcher's emotional wellbeing, (2) how those risks can be mitigated in the research process, and (3) whether formal or informal opportunities for debriefing emotional demand can be created within the research process. Moncur also suggests that individual researchers should have self-care strategies in place, that institutions should provide access to therapeutic support, and that researcher wellbeing plans be made explicit in the ethical approval process.

In our case, reviewing Moncur's recommendations inspired us to create a formal space to debrief emotional demands within our ongoing research process, operationalized in the 15-minute sessions added to our regular meetings. Moncur's recommendations also inspired us as individuals to prioritize self-care practices, including seeking out grief-specific counseling and therapy available at our academic institution. Unfortunately, our study design processes (e.g., our IRB application), and our informal disciplinary norms, did not require or expect us to have a wellbeing plan in place for conducting this research. In fact, we did not even consider the emotional burden of this research in advance of our data collection, due to the computational nature of the work. Because we had not encountered emotional duress in our previous computational research, and because no previously-established infrastructure or norms prompted us to consider a wellbeing plan, we mistakenly assumed that the computational nature of our work would allow us to keep an emotional distance from our sensitive subject matter. While our adaptations effectively improved our wellbeing, having pre-established guidelines or disciplinary norms to guide our research would have been highly beneficial and would have mitigated additional harm. To support future research studying vulnerable populations whose researchers may be at risk of harm, we extend Moncur's suggestions for qualitative researchers by offering the following recommendations for computational researchers.

Have a Plan in Place During Initial Study Design Perhaps the most obvious recommendation is for researchers to have a wellness plan in place at the outset of a study. It may be easy to assume that wellbeing challenges can be dealt with on a case-by-case or person-by-person basis. However, an ad hoc response to wellbeing challenges has the potential to make it so challenges only get addressed in instances of crisis – necessitating a hasty and reactive response instead of a well-measured proactive response. A plan, regardless of how sparse, is preferable to no plan at all. We believe that wellbeing plans amongst computational researchers should be normalized and embedded into the initial study design of every study we conduct, before any data collection is started.

Slow Down Data Collection and Analysis Computational methods are powerful in part due to their potential data collection and analysis speed. We believe that the quick computation speed in studies researching certain sensitive content may actually outpace the emotional processing capacity of research team members. Without proper time to reflect, sensitive content can compound trauma responses in team members. By slowing down the research process – allowing time for researchers to personally process and come to terms with the intensity of the data – researchers can more effectively identify the areas that are exerting emotional demands and come up with individualized plans to seek out support. In our case, we slowed down our research process by moving our weekly meetings to bi-weekly meetings. During manual coding, we additionally limited the number of posts we were manually coded to a handful per week. These were easy and simple changes that did not change our overall research trajectory or publication goals. In fact, the additional time provided other benefits, such as a deeper engagement with our data. There are many ways – simple and complex – that a computational study can 'slow down' to allow for more intentional and meaningful processing of emotionally demanding content. However, regardless of the tact taken to slow down, we recommend that researchers resist the urge to conduct their research at a breakneck pace and instead allow for more intentional time to emotionally process the inputs and outputs of their data collection and analysis. Although conference submission deadlines are realities that inform our research processes – and one can especially imagine the very real pressures on graduate students to publish as quickly and prolifically as possible – we should do what we can to resist the urge to let these deadlines take precedence over our wellbeing.

Embed Formal Debrief Spaces *Within* the Process Establishing a formal debrief space in our meetings was critical to combating feelings of isolation amongst research team members. Intentionally maintaining a formal debrief space within the research process helped members communicate – reducing feelings of shame and hopelessness. Put simply, the space allowed people to feel less alone. One function of feeling less alone was that members felt more empowered to seek external support. Though I am not arguing that creating a formal debrief space should be universally deployed in all cases, based on our experience, I believe it may be useful for computational research teams to at least consider the creation of such formal spaces in their research process.

Certainly, there are challenges to creating a formal debrief space. One can imagine that formal spaces can quickly shift from research spaces into therapy spaces. It is inappropriate for research debriefing spaces to become therapy spaces. Lead researchers are typically not trained therapists and do not have therapeutic skill sets. Even if a lead researcher *is* a trained therapist, their professional role on a research team is not to provide therapy. Allowing the debriefing space to slip into a therapy space could potentially cause additional harm or a breakdown of professional boundaries. Therefore, when deployed, we recommend that formal debriefing spaces incorporate a clear list of expectations for the goals (e.g., to identify emotional demand and adapt research practices to improve wellbeing), procedures (e.g., first we will discuss the emotional impact of the data collection, then we will...), and boundaries of the space (e.g., this is *not* a space to process your own traumatic experiences).

A further challenge to providing formal debrief spaces is that the support needs of research team members may vary wildly. For example, a 20-year-old undergraduate research assistant will presumably have a very different set of experiences researching bereavement than a PI who has been reading online bereavement posts since the advent of Facebook. While the undergraduate may developmentally need certain specialized support, the faculty member may not – or may need very different specialized support. An open question for determining effective support is how to account for that diversity of experience. Beyond diversity of research experience, one can also imagine the impact of diverse cultural backgrounds, personal identitie, and personal experiences, as areas where differential support may be needed. Creating practices in formal spaces that can provide differential support based on diverse identities and experiences may be a prudent strategy. However, more work is needed in this area.

Finally, there is the risk that the establishment of a formal debrief space may not be appropriate as it could be perceived as coerced disclosure for research team members. Though in the context of our research team a formal debrief space was a helpful and useful approach, this may not be the case across all kinds of research teams or academic contexts. One can imagine the dangerous power differential of a senior PI unintentionally creating a space in which their students feel an expectation to disclose personal trauma – or feel as if their willingness to express vulnerability is tied to their status on the project. With these challenges and risks in mind, researchers should exert caution when creating a formal debrief space. However, our findings suggest that a formal debrief space within the research process can be a helpful tool for computational researchers conducting emotionally demanding research – and should at least be considered as a possible strategy to improve researcher wellbeing.

The Onus of Academic Institutions to Support Researcher Wellbeing

Researcher wellbeing support cannot be fully addressed without institutional transformation – whether that be in our formal processes or our interdisciplinary norms. Throughout our study, we were struck by how little support was readily available from the academic institutions we sought resources from. For example, retrospectively, the lack of an IRB request to have a wellbeing plan at the study's outset was detrimental to our ability to adapt to emerging challenges. Similarly, we found the lack of institutionally and/or department-sponsored training for researchers conducting computational research on vulnerable populations concerning. This is not an indictment of the specific institutions we sought resources from. Rather, the lack of support is symptomatic of much wider infrastructural and cultural challenges we as an academic community must address to improve researcher wellbeing – requiring additional discussion and intentionality about what strategies are appropriate to address those challenges.

Regarding improving IRB processes – certainly IRBs are much more concerned about participants than they are about researchers, originating from a complex history of needing institutional regulations that protect vulnerable populations from researcher harm. Although I am not arguing that IRBs should reorient their purpose away from protecting participants, I am suggesting that the academic community should continue to consider how the IRB might additionally protect researchers when conducting emotionally demanding work. Building on previous work examining tensions in what ways IRBs should support emotionally demanding qualitative research (Dickson-Swift et al. 2008), future research is needed to determine what institutional support should look like for computational researchers conducting emotionally demanding work. Regardless of what strategies are taken, our findings suggest that to mitigate harm to computational researchers conducting emotionally demanding research, it is important for institutions to consider possible avenues to make policy and process decisions that might normalize and institutionalize proactive wellbeing practices for researchers.

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